Understanding User Behavior in the Wild Using Smartphones

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Contents

Abstract

The ubiquity of smartphones offers a unique lens for studying human behavior in natural settings. Smartphone sensing, an expanding field driven by the widespread use of sensor-rich smartphones, facilitates observation and analysis

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of natural, “in-the-wild” behavior. These devices enable the seamless and unobtrusive collection of data across a broad spectrum of behavioral aspects, such as physical movement, social interactions, and smartphone usage patterns. This chapter provides an overview of smartphone sensing for understanding user behavior, outlining the types of sensors found in smartphones, such as motion and interactivity sensors, and their applications in capturing diverse aspects of user behavior. It also discusses the methodologies for data collection, distinguishing between passive and active sensing, and summarizes methods for data preparation and analysis in extracting meaningful insights from the raw sensor data. The practical applications of smartphone sensing are explored across multiple domains, including health monitoring, education, and social behavior analysis, demonstrating its versatility and potential to inform and enhance various aspects of daily life. The chapter also addresses the challenges inherent in conducting in-the-wild studies, such as ensuring data quality, maintaining participant engagement, and navigating technological constraints. Ethical considerations, particularly regarding privacy, informed consent, and data security, are highlighted as critical components of responsible research in this field. Looking ahead, the chapter identifies areas for future research, including the refinement of data collection and analysis methodologies and the ethical implications of advanced and developing sensing capabilities.

Keywords

Smartphone sensing · User behavior · In-the-wild study · Data analysis · Machine learning · Data ethics

Introduction

The proliferation of smartphones in recent years has not only transformed the way we communicate and interact with the digital world but has also opened up avenues for understanding user behavior in natural, “in-the-wild” environments. These devices, which have become ubiquitous in everyday life, are equipped with a plethora of sensors and advanced functionalities. These capabilities facilitate the collection of a wide range of sensor data in a continuous, unobtrusive manner, commonly referred to as smartphone sensing. Smartphone sensing enables unique opportunities to observe and analyze human behavior in its most natural state, including aspects such as physical movement, social interactions, and smartphone usage patterns. Over the past two decades, research has increasingly focused on leveraging these devices to capture and analyze various facets of human behavior. This growing body of work demonstrates the vast potential of smartphone sensing, in terms of both its technical capabilities and its applications across diverse fields.

Early studies in smartphone sensing primarily focused on tracking basic physical activities, such as walking, running, and cycling, using accelerometers and GPS sensors. These sensors allowed researchers to monitor patterns in users' movement and physical activity levels, offering insights into health and fitness. Over time, the advancement of smartphone technologies has allowed the scope of smartphone sensing to expand and capture more complex behaviors across various domains. These applications include areas such as:

- **Health and Wellbeing:** Smartphones are increasingly being used to monitor and manage physical and mental health. Sensors such as accelerometers and gyroscopes help track physical activity and sleep patterns, while GPS is used to analyze movement patterns and exposure to different environments. Mental health studies have harnessed smartphone-based data to monitor behaviors linked to stress, anxiety, and depression, using digital biomarkers such as communication frequency and typing behavior.
- **Education:** Smartphone sensing has been used to monitor student behavior and engagement with education, such as tracking their physical movement across campus with GPS data or analyzing app usage patterns to understand study habits. This can help educators tailor interventions to improve time management and focus, or design campus spaces to better meet student needs based on resource usage.
- **Social Behavior:** By capturing data on smartphone usage, such as call and text logs, social media activity, and location data, researchers can examine patterns of social behavior and interaction. This has been particularly useful in understanding the impact of social networks on wellbeing, as well as how individuals form and maintain online relationships.

As smartphones continue to advance, the scope of smartphone sensing research expands alongside them. Innovations in machine learning and data processing now allow for deeper and more meaningful insights to be extracted from sensor data, pushing the limits of how researchers can study and understand human behavior.

This chapter provides an overview of developments in smartphone sensing. It first introduces different types of smartphone sensors (refer Fig. 1) and sensing methods used for in-the-wild studies, presenting the functionalities and applications of each. Following this, the chapter explores data preparation and analysis strategies for transforming sensor data into insights. It presents various machine learning techniques for analyzing large and complex datasets to distill behavioral information and discusses the practical applications of smartphone sensing in various fields. Finally, the chapter discusses the challenges associated with conducting in-the-wild studies and provides recommendations for how to effectively manage these challenges to achieve successful study outcomes. These include strategies for improving sensing technology and suggestions for participant interaction. Ethical considerations in smartphone sensing are also examined, highlighting the importance of ethical practices in in-the-wild smartphone-based research. Strategies for maintaining participant trust and confidentiality are highlighted, along with methods for protecting sensitive information.

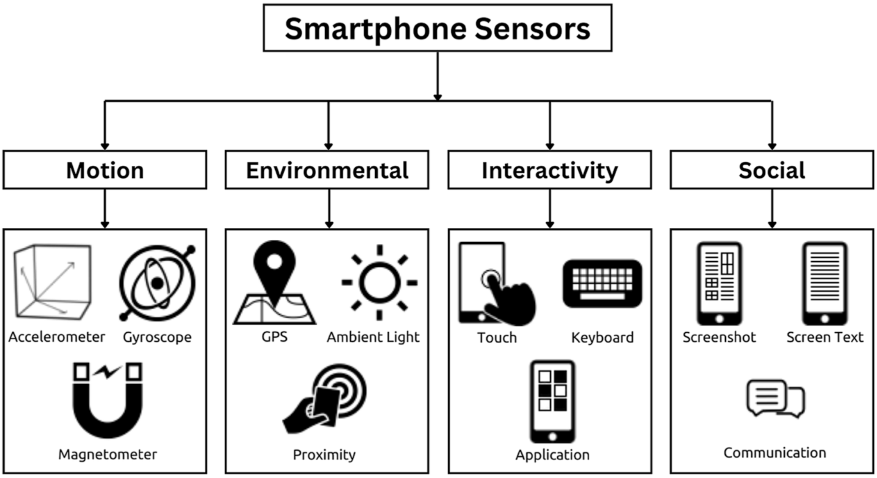

Fig. 1 Smartphone Sensor Taxonomy. (Images edited and sourced from Ferreira et al. 2015)

Smartphone Sensors for Capturing User Behavior

Smartphones have evolved significantly over the last decade, emerging as versatile devices containing a wide array of powerful sensors. These sensors allow smartphones to perceive, analyze, and interact with the world. The ability of smartphones to capture vast amounts of data from everyday use facilitates a wide range of benefits for people across various domains. As a result, many everyday consumer and research-oriented products for smartphones heavily depend on this sensor data and the insights they generate. Due to the intricate nature of studying user behavior, analysis of sensor data often takes on a multifaceted approach by combining data from multiple sensors that each capture a different aspect of human activity. Although these sensors serve distinct purposes and functionalities, they can be broadly categorized based on their underlying technologies and application areas.

Motion Sensors

Motion sensors in smartphones are integral to enabling movement-based functionalities, allowing them to detect and respond to changes in movement, orientation, and acceleration. These sensors enable a wide range of applications, from controlling tilt-based games to health-related features such as physical activity detection. There are several key types of motion sensors found in smartphones, each with its specific technology and purpose.

The accelerometer consists of small, sensitive mechanical structures that react to acceleration. When the smartphone experiences motion or changes in orientation, these structures generate electrical signals that are then processed by the device's central unit. This data provides information about the device's acceleration in three dimensions (X, Y, and Z axes), which can enable features like adjusting the screen orientation based on how the device is held and tracking the user's step count.

Gyroscopes work in tandem with accelerometers to provide precise orientation, angular velocity, and rotational data. Angular movement or rotation of the smartphone is captured as signals and processed by the smartphone's software, which can detect the rate of rotation or angular velocity and the orientation of the movement. This precise data can be utilized to enhance various smartphone functions, including image stabilization by reducing the effect of camera vibrations when capturing photos and videos, and tracking the position and orientation of a smartphone in real time to enable augmented reality tools.

Additionally, magnetometers, built upon magnetic sensor technology, detect changes in the Earth's magnetic field. This enables the smartphone to determine its orientation relative to magnetic north, serving as a digital compass. When a smartphone changes its position or orientation, the magnetometer detects alterations in the local magnetic field's strength and direction. Data collected from magnetometers can be applied in compass applications and navigation, aiding users in finding their way, determining directions, and providing geographical context.

Environmental and Location Sensors

Understanding the user's surroundings can provide personalized user experiences by adjusting the smartphone's behavior based on their location and environment. Location sensors can provide precise geospatial data, enabling a range of location-based services such as map navigation. Capturing the smartphone's surroundings can be facilitated by environmental sensors, which detect and measure various environmental factors, contributing to a range of context-aware applications and functionalities. By gathering data about ambient conditions, these sensors enable the device to adapt to its environment, including enhancing screen readability and phone calls. These functionalities are each enabled by a different smartphone sensor.

GPS sensors are ubiquitous in smartphones, playing a pivotal role in enabling location-based services. These sensors receive signals from satellites orbiting the Earth to accurately pinpoint the user's geographical coordinates. The power of GPS technology on smartphones allows for precise and real-time location determination, which can be integrated with other services. From turn-by-turn navigation and location sharing to geotagging photos and finding nearby restaurants, GPS sensors provide a wide range of assistance for everyday travel. These sensors also allow for studying how people travel and their movement patterns, which can be applied in various domains such as health and marketing.

Ambient light sensors detect and measure the intensity of light in the device's vicinity. This information is then used to automatically adjust the screen brightness based on the smartphone's surroundings, ensuring visibility while conserving battery life. In well-lit environments, the screen brightness increases, while it decreases in low-light conditions. Adjusting screen brightness automatically can benefit users by reducing eye strain, offering convenient readability under varying lighting conditions, and extending battery life when the screen is dimmed.

Proximity sensors commonly use infrared sensing to detect the presence or absence of objects in close proximity to the smartphone, using the amount of reflected light to determine distance. Their primary application is to turn off the touchscreen during phone calls to prevent accidental touches. By sensing when the device is close to the user's ear or face, proximity sensors help prevent actions such as unintentionally ending a call, and automatically turning the screen on and off can also save battery life. Additionally, they can be used to detect air gestures and enable object detection for augmented reality applications.

Interactivity Sensors

Interactivity sensors in smartphones capture user interaction, allowing users to alter the smartphone's behavior based on their activity. These sensors often behave as software derived from other sensor data, synthesizing these data to interpret user activity and input. Through these sensors, users can navigate through applications, input text and commands, and execute various gestures. Because these sensors detail user interactions with their smartphone, they can also be used to study user behavior in relation to their smartphone use, including smartphone addiction or patterns in app usage.

Touch sensors provide one of the fundamentals of smartphone interactivity. Touchscreens can detect the position of a user's touch on the screen, and their multitouch capabilities allow for various gestures, such as tapping, swiping, and zooming. These sensors enable users to navigate through apps, access menus, and interact with content. Touch sensors can be used to study how frequently people tap various parts of a phone screen, providing suggestions for app design.

Building upon touch sensors, keyboard sensors can be used to capture both typing dynamics (e.g., duration between key presses) and the character/semantic content inputted by the phone user. One possibility is to implement a keyboard sensor such that there is the option to mask the characters that are input (for example, replacing every alphabetic character with the letter "a"). In this way, keyboard typing dynamics could still be captured in cases where there is a desire to not share/store what character content the user is typing.

Another dimension of interactivity can be revealed through the analysis of application usage patterns. By tracking app usage with the application software sensor, researchers can glean insights into the duration of app usage, the sequence in which apps are accessed, and the frequency of app switches. This data provides a window into the user's digital habits and preferences, providing insight on which applications are most valued and how they fit into the user's daily routine. For instance, heavy usage of productivity apps during work hours might indicate professional use, while increased activity on social media or entertainment apps in the evening could suggest recreational use. Additionally, app usage data can also highlight trends in digital behavior, such as the adoption of new apps or changes in the usage of existing ones. This can be particularly valuable for developers and marketers seeking to tailor their products to meet evolving user demands.

Smartphone screenomes have been developed as a means to comprehensively document all smartphone interactions, aiming to offer deeper insights into the content users engage with or consume. Screenomes are created by taking high-frequency screenshots, typically every few seconds, to record the digital interactions of individuals on a day-to-day basis, thus enabling a detailed examination of how they navigate the digital environment. The Screenomics framework has conducted in-depth studies of screenomes, utilizing techniques like optical character recognition (OCR) and image analysis to decode textual and visual information from these screenshots (Reeves et al. 2019).

Recent work on a new screen text sensor exemplifies how existing smartphone functionality (in this case the Android accessibility services) can be utilized/repurposed in developing further sensor possibilities. This screen text sensor aims to capture all smartphone interactions through collecting textual information directly from the screen in real time (Teng et al. 2024a). Data is collected whenever the sensor is activated, enabling the capture of even brief interactions while simultaneously reducing computational demands. By analyzing screen text data in conjunction with other sensors such as location, a more nuanced understanding of the user's overall behavior can be captured.

Social Sensors

Social smartphone sensors are a category of sensors and data collection mechanisms that provide insights into the user's social behavior and interactions. Unlike traditional physical sensors like accelerometers or GPS, social sensors analyze patterns and metadata from communication apps, social media usage, and other collaborative platforms to understand social dynamics and relationships.

Communication sensors, such as call logs and text messages, can provide insights on an individual's personal routines and preferences through the lens of their social interactions. The timing of calls and messages can reveal patterns that align with the user's daily schedule, such as increased activity during certain hours that may coincide with their commute or leisure time. This temporal data can indicate when individuals are most likely to engage in social interactions, offering insights into their preferred times for communication. Personalized marketing, for instance, can leverage the understanding of an individual's daily routine and peak times of social interaction for tailoring communication strategies to reach them when they are most receptive. Additionally, analyzing call and text message data across different user groups can uncover cultural norms and societal trends in communication. The average length of phone calls and the times of day when communication peaks can vary significantly across cultures, age groups, and social circles, reflecting the diverse ways in which people integrate mobile communication into their lives. This understanding could aid the design of technology and communication tools, providing more inclusive and adaptable platforms that cater to the needs and preferences of different user groups.

Similarly, the use of the screen text sensor and screenomes can also reveal the behavior of users across various communication platforms such as social media sites. Analyzing interactions with others on social media offers a broader perspective on user behavior and social dynamics, capturing not only what users post and share, but also the context and timing of these interactions. Moreover, the patterns of social media use, including peak activity times, types of content shared, and the diversity of interactions, can mirror an individual's social preferences and habits in real-life settings. Someone who is very active and engaging in online discussions might be similarly sociable and outspoken in physical social settings, while a preference for passive content consumption could suggest a more reserved nature. This behavioral analysis can also extend to understanding the impact of social media on an individual's social wellbeing. For example, the sentiment of the content users interact with may be correlated with one's personality traits and sociability.

Data Collection Methods

The capabilities and versatility of smartphone sensors enable data to be collected in many ways. Although there exists a range of data collection methods for smartphones, their characteristics can be largely grouped into two categories: passive sensing and active sensing. This division reflects the distinct approaches toward gathering information about user behaviors, preferences, and interactions with smartphones. Passive smartphone sensing encapsulates the continuous and unobtrusive collection of sensor data, allowing for capturing information that aims to reflect users' natural activities. On the other hand, active smartphone sensing describes data collection initiated by specific user actions or inputs, enabling targeted and contextually relevant observations. Passive and active sensing methodologies can also be used in tandem, allowing researchers and developers to tailor their data collection approaches based on the requirements of their task. This demonstrates the adaptability and richness of smartphone sensing in capturing the multifaceted nature of user-device interactions.

Passive Sensing

Modern-day smartphones facilitate not only elementary tasks such as communication and web browsing, but also serve as collections of powerful sensors capable of capturing and analyzing a myriad of user data. Passive smartphone sensing has been commonly used to capture this data, where the smartphone collects data on its own without interfering with the user's smartphone activities. The unobtrusive nature of passive sensing enables the continuous collection of data from various sensors without necessitating explicit user interaction or initiation. These sensors, ranging from accelerometers and gyroscopes to GPS and proximity sensors, can combine to form a complex network that captures diverse aspects of user interaction. The uninterrupted flow of data allows for an in-depth observation of users' behaviors over extended periods, offering researchers and developers a nuanced understanding of their engagement with smartphones.

A primary benefit of passive sensing is its unobtrusiveness, enabling data collection while allowing users to use their smartphones naturally without being disturbed. This minimizes the need for user involvement in the data collection process, allowing for a more accurate representation of natural user behavior. The ability of passive sensing to autonomously gather data in the background alleviates the reliance on users to actively facilitate data collection, resulting in a reduced burden on users and a substantial decrease in the likelihood of missing data due to inconsistent engagement or forgetfulness. Additionally, passive sensing allows data to be captured continuously unless manually interrupted, providing a closer resemblance of user behavior when using their smartphones and empowering the application of advanced techniques to model user behavior over extended periods.

Active Sensing

In contrast to passive sensing, active smartphone sensing describes the collection of data initiated by specific user actions or captured from user responses. This methodology provides a focused lens, enabling researchers and developers to capture contextually relevant observations. Unlike passive sensing, where data is collected continuously in the background, active sensing relies on intentional actions such as taps, responding to surveys, or other explicit inputs from the user. These interactions serve as triggers, prompting the device to engage specific functionalities or request a user response, thereby capturing data relevant to the user's immediate task or goal.

The intentional nature of active sensing extends beyond traditional sensor interactions to include methodologies like surveys and the Experience Sampling Method (ESM). Surveys prompt users to respond to predefined questions, offering researchers a structured means of gathering intentional and subjective data. ESM, on the other hand, involves asking individuals to provide systematic self-reports at random occasions during their daily lives. ESM aims to measure participants' behavior, thoughts, and feelings throughout their day-to-day activities and is conducted via answering short questionnaires throughout the day (van Berkel et al. 2017). These questionnaires are answered by users in situ, allowing closer replication of natural behavior than a controlled lab study. The use of surveying methodologies contributes valuable first-hand insights into user sentiments and preferences, enriching understanding of user behavior. ESM has been widely used in various fields, such as providing ways to capture momentary mental states and emotions in the context of daily life (Stamate et al. 2017). It has also been used to advance personalized healthcare by capturing individuals' moods, symptoms, and experiences in real time (Bos et al. 2019). The growth of mobile technologies has made ESM more efficient and accessible, and delivering them via smartphones is both low cost and easily accessible. By scheduling times for questionnaire delivery without requiring user initiation, ESM aims to reduce the burden of data collection on users while maintaining the timeliness and relevance of the data.

While active smartphone sensing offers precision in capturing intentional user inputs, balancing the need for user-initiated data collection with privacy considerations is paramount. Clear communication with users about data usage and ensuring explicit consent for allowing active sensing are critical to maintaining trust. Moreover, the frequency and duration of user-initiated sensing should be implemented such that the necessary data can be collected while respecting the availability of participants. To reduce participant burden, participants may be provided with an option to skip or snooze a questionnaire if they are unavailable. This can simultaneously inform researchers that the participant is busy during particularly times in the day or week, which itself could be a measure of behavior.

Active smartphone sensing plays an important role in collecting data through deliberate user interactions with their devices, offering focused windows for gathering information. Alongside the array of sensors embedded in smartphones, active sensing provides detailed insights into user behavior that are specific to particular tasks or contexts. By combining passive and active sensing, smartphone data can offer a holistic view of how users engage with their devices.

Sensing Applications

Various sensing applications have been developed to facilitate smartphone sensing for diverse purposes, ranging from general sensing apps to more specialized tools such as ESM-specific platforms. Misc (2024) provides a comprehensive repository of available sensing tools and their characteristics. These smartphone sensing applications, along with several others, leverage the sensor capabilities of smartphones to simplify the data collection process for researchers. Although the functionalities of existing apps are applicable to most study types, more specialized studies may require the development of new sensing applications to better suit their needs.

Methods for Analyzing User Behavior

Data Preparation

Data preparation is a fundamental and critical step in the processing and analysis of raw smartphone data. Using smartphone data for understanding user behavior often consists of categorization, prediction, and recommendation, among many other methods. For machine-learning-based techniques, the quality of these analyses is directly dependent on the quality of the training data, and having noisy or biased data can generate results unrepresentative of real-world behavior. Common sources of smartphone sensor data include the aforementioned accelerometers, gyroscopes, and GPS. Real-world data collection from these sensors introduces various sources of noise, such as different methods used for sensor calibration, sensor malfunction, or participant noncompliance, which can lead to inconsistencies and gaps in the data. This, in turn, can significantly impact the accuracy and reliability of subsequent analyses. To tackle this issue, raw smartphone data is captured and processed using data preparation techniques. Data preparation encompasses several key stages, including data acquisition, preprocessing, transformation, and feature extraction. Each of these stages plays a crucial role in transforming raw sensor data into meaningful information for analysis.

The first step of data preparation is data acquisition, where information is collected from various smartphone sensors. These sensors often collect data in different formats and at various frequencies due to the nature of each sensor (Leu et al. 2018). For example, certain studies may necessitate continuous accelerometer monitoring to detect precise movement but may only need to capture the user's location every 10 minutes. Because this raw data is captured in the wild from multiple sources and at different frequencies, it often contains noise and artifacts due to factors like variation in smartphone hardware and the user's environment. Therefore, it is essential to apply data cleaning techniques to preprocess this data before it can be used for analysis. Despite these inconsistencies in data structure and content, considerations such as optimizing data collection intervals and applying consistent standards for sensor calibration can still be utilized to reduce noise present in the raw data (Grammenos et al. 2018). In doing so, this may improve data quality and reduce the amount of preprocessing required.

Once the required data has been collected, it is treated through data preprocessing. Preprocessing aims to clean and standardize the data, allowing it to be further analyzed. This step involves, firstly, checking the dataset for errors, missing values, and outliers, which are common in raw data. Errors in a dataset can arise from various sources such as incorrect data entry, measurement inaccuracies, or data transmission issues. For example, values recorded in Fahrenheit within a dataset of temperatures recorded in Celsius would be considered errors. Missing values occur when no data value is stored for a variable in an observation. This can happen for several reasons, such as equipment failure or respondents not answering certain questions in a survey. Outliers are data points that differ significantly from other observations and can naturally occur as the result of variability in the measurement or could also indicate experimental errors. Outliers can influence statistical analyses significantly, often leading to misleading results.

After identifying errors, missing values, and outliers, various strategies can be employed to deal with them. Errors could be corrected if the original data source is available, or erroneous data may be excluded from the analysis. Handling missing values can involve imputation methods using techniques such as Generative Adversarial Networks (Luo et al. 2018), where missing data is replaced with substituted values. Otherwise, observations with missing values from the analysis can also simply be excluded. Outliers may be investigated to determine if they are legitimate observations or if they result from errors; legitimate outliers might be kept, while those resulting from errors could be excluded or corrected. The chosen method depends on the nature of the data and the specific analysis being performed.

The cleaned data then undergoes transformation and normalization. These steps involve restructuring the data into a format that is more suitable for analysis. This could involve converting data types, such as changing timestamps into a standardized format, or encoding categorical variables for machine learning models. The specific transformation process is greatly influenced by the nature of the data and the goal of the subsequent analysis. For instance, Natural Language Processing (NLP) techniques are essential in working with textual data, such as understanding texting behavior on smartphones or studying social media interaction (Gutierrez et al. 2021). This often starts with tokenization, breaking text down into smaller units like words or phrases, and may extend to removing stop words, stemming, and lemmatization to refine the text for analysis. Vectorization techniques, such as TF-IDF or Word2Vec, then convert this refined text into numeric forms that machine learning models can process (Rustam et al. 2019). Following transformation is the process of normalization, which is necessary for dealing with data from multiple sensors operating on different scales. Normalization adjusts these diverse data values to a common scale (del Rosario et al. 2015), ensuring that variations in the data accurately reflect differences in user behavior, rather than discrepancies in sensor measurements. This step is particularly crucial for comparative analysis and for preparing data for use in machine learning algorithms.

Following data formatting, feature extraction is used to extract significant information from the data. This step can reduce data dimensionality, retaining only a portion of the original attribute set. By doing so, feature extraction simplifies the dataset, highlighting the most informative elements and diminishing the influence of less pertinent features. For instance, extracting features like the peak frequencies of accelerometer data over various time periods can help identify when a user is walking, running, or cycling (Bayat et al. 2014). Within social and behavioral studies, feature extraction may focus on highlighting communication patterns, such as the frequency and timing of calls or messages, or the number of different apps used over a given period. In doing so, features that do not directly contribute to these measures may be discarded to improve analysis.

Each of these steps plays a vital role in ensuring the quality and reliability of smartphone data for subsequent user behavior analysis. However, it is important to note that not every task necessitates the implementation of all these steps, and depending on the specific objectives of a study, additional steps might be required. The goal of preprocessing is to generate a dataset that accurately captures the fundamental behaviors and patterns in a format suitable for analysis, which can be achieved in multiple ways.

Data Analysis Techniques

Once the smartphone sensor data has been prepared, various techniques can be applied to analyze this data and gain insights into user behavior. These techniques transform raw data into insights for various applications, from health monitoring to environmental sensing. Machine learning is the most widely used technique for interpreting and extracting meaningful information from smartphone sensor data, offering multiple methods each suited for a range of applications (Qiu et al. 2022). These methods are effective at handling the high-dimensional and often noisy data generated by smartphones, and multiple machine learning methods are often used in conjunction to improve performance.

One prevalent method for analyzing smartphone sensor data is supervised learning, which involves training a model on a labeled dataset to predict outcomes based on new, unseen data. For example, decision trees can be used for activity recognition, where sensor data like accelerometer and gyroscope readings are used to classify user activities such as walking, running, or sitting (Nematallah et al. 2019). Supervised learning can also be applied for emotion recognition, where factors such as phone usage habits and communication frequencies can help infer a person's emotions. By analyzing these sensor inputs, machine learning models such as support vector machines (SVMs) can detect and predict the user's emotional state (Jaques et al. 2015). Similarly, applications in health monitoring often use these methods to identify health markers based on sensor data such as physical activity. For example, accelerometers and GPS can collect data on user activity levels and locations. Random forests, a form of supervised learning, can be trained on this data to classify different physical activities or to predict health metrics (Lee and Kwan 2018). These insights can then be used to provide personalized fitness advice, track health progress, and alert users to potential health issues.

Another common machine learning method for smartphone data analysis is unsupervised learning. Whereas supervised learning uses labeled training data, unsupervised learning is utilized when there is no labeled data available. Without given labels, unsupervised learning methods aim to discover any underlying patterns and relationships within the dataset, without explicit guidance. Clustering algorithms are used to group similar data points together, which can be particularly useful in identifying patterns or anomalies in sensor data without predefined categories. For example, clustering methods such as time-based clustering can identify places of interest (POIs) based on GPS data, where data points representing user locations are clustered to infer frequently visited places (Lv et al. 2012), which can be used for real-time location-based services and recommendations. Association rule learning, a method for discovering relationships between variables, can also be applied to sensor data to uncover habitual patterns or correlations in smartphone usage. For instance, mining association rules from location and app usage data can reveal patterns in user behavior, such as the tendency to use certain types of apps in specific locations or at particular times (Tseng and Hsu 2014). This insight can be used to develop smarter app recommendation systems or to optimize smartphone settings automatically based on the user's context and habits.

Deep learning is a powerful technique for processing complex sensor data. It uses neural networks, which mimic neural structures in the human brain, to discover patterns and make predictions about new data, iteratively improving the model and its predictions. Transformer models are a form of neural networks commonly used for training large corpora of text data and generating language. Introduced by Vaswani et al. (2017), transformers have become the foundation for many state-of-the-art natural language processing (NLP) models. These include large language models (LLMs) like ChatGPT and have been further applied to tasks beyond text such as computer vision and audio processing. One of the most influential transformer models is BERT (Devlin et al. 2018). BERT is designed to pretrain deep bidirectional representations from unlabeled text, allowing it to capture the context and meaning of words in a sentence with high accuracy. BERT is widely used in sentiment analysis, which involves determining the sentiment or emotion expressed in a piece of text, and can be applied to various domains such as understanding texting and social media use (Nandwani and Verma 2021). Deep learning is also applied in the analysis of user behavior and context awareness. By analyzing sensor data such as GPS and light, deep neural networks can predict the user's context and enable smartphones to automatically adjust its settings or provide relevant information based on the user's current activity or environment (Nweke et al. 2018). For example, a smartphone could automatically switch to a driving mode when it detects that the user is in a car (Liang et al. 2020), optimizing navigation and reducing user burden. Additionally, emotion recognition commonly employs deep learning methods for classification. LSTM (Long Short-Term Memory) networks, a form of RNNs, can synthesize data captured from the user's camera, microphone, and keyboard to recognize emotional states (Yang et al. 2023). Similarly, classification networks and LLMs can also be used to predict affective states based on typing behavior (Wampfler et al. 2020), communication patterns (Zhang et al. 2024), and the content that users view on their smartphones (Teng et al. 2024b).

After a machine learning model has been trained, it is evaluated using validation methods. This phase, encompassing techniques like cross validation, is fundamental in assessing the model's ability to generalize beyond the training data. Cross validation involves systematically partitioning the data to test the model on different subsets, thereby safeguarding against overfitting and assisting in the fine-tuning of the model's parameters. This step is crucial in confirming the model's readiness for deployment in real-world scenarios. The choice of cross-validation strategy plays an important role in developing robust models. k-Fold cross validation, where the dataset is partitioned into k equally sized segments and the model is trained and tested k times using a different segment as the test set in each iteration, offers a balanced approach between maximizing data utilization and computational efficiency. However, when dealing with human behavioral data, which occurs in distinct time-segmented patterns, specialized methods like Leave-One-Subject-Out Cross Validation (LOSO CV) and Time Series Cross Validation can be more effective. LOSO CV, where each iteration of validation involves using all data from one subject or participant as the test set and the data from all other subjects as the training set, accounts for the variability between individuals and groups the set of behavioral traits unique to each person (Long et al. 2009). This is essential for smartphone sensing data as individuals exhibit large differences in behavior. Time Series Cross Validation, which involves progressively using earlier data subsets for training and later subsets for testing, is essential for preserving the chronological order of data (Bergmeir and Benítez 2012). This method ensures that the predictive models are always tested on future data, simulating real-world scenarios where predictions are made on unseen future events based on past data. These specialized validation strategies can be used to address the unique challenges posed by human behavioral data, such as its sequential nature and inter-user variability, leading to the creation of predictive models that are highly generalizable across different types of smartphone sensing studies.

Practical Applications

Although smartphone sensors are capable of capturing a diverse array of data, individual sensors often offer limited insights into user behavior when analyzed in isolation. Therefore, analyses frequently necessitate the amalgamation of data from multiple sensors, known as data fusion. Data fusion is the integration of information from multiple sensors to enhance the precision and reliability of the analysis. By combining data from complementary sensors within a single smartphone, such as merging accelerometer data with GPS information, it can allow for a more comprehensive understanding of user behavior (Berrouiguet et al. 2018). This understanding can also be used to inform recommendations based on the user's context and has been studied extensively across various domains.

Smartphone sensor data is increasingly leveraged in health and wellbeing. Digital phenotyping research, for instance, has demonstrated the potential of using GPS in combination with other sensors like light and cell tower data to evaluate social interactions (Huang et al. 2016) and mental health conditions (Wahle et al. 2016). Similarly, the analysis of accelerometer data, along with the gyroscope and magnetometer information, can be used in identifying physical activities (Weiss et al. 2016) and monitoring sleep patterns (Montanini et al. 2018). Furthermore, the use of smartphone applications and communication logs offers valuable context for health assessments, including monitor mental health (Servia-Rodriguez et al. 2017). Keystroke dynamics on smartphones also offer a method for assessing users' typing patterns to deduce their contextual and behavioral information. Tahir et al. (2022) have shown that machine learning techniques applied to keystroke and character input data can accurately identify emotions such as happiness, sadness, and anger from brief text entries. The examination of keyboard-generated text also facilitates the analysis of typing errors and the timing of keystrokes, suggesting that stressed individuals often type more quickly and make more mistakes (Ciman et al. 2015). These digital traces enrich our understanding of user engagement with various types of content, contributing to the development of tailored health recommendations and interventions.

Smartphone sensing technologies have also been widely applied within education. The WoBaLearn system takes advantage of the smartphone's ambient light sensor and microphone to provide educational content in a work-based learning setting, customizing support to match the unique learning requirements, traits, and contexts of each student (Zhang et al. 2015). Similarly, the CALMS framework makes use of GPS information along with other contextual data, such as students' academic backgrounds and temporal factors, to present academically pertinent content, a strategy that has been linked to improvements in student performance and satisfaction levels (Erazo-Garzon et al. 2019). Additionally, a method that employs GPS data to power a personalized, context-aware learning recommendation system alerts students to relevant learning resources in their vicinity based on their geographical position (Yao 2017). Using the flipped classroom model, Louhab et al. (2019) gathered data from students' mobile devices, including details about installed applications, screen dimensions, battery status, and Internet access, to determine the most suitable format for course material distribution. The feedback from students who interacted with this context-sensitive system indicated a high level of satisfaction with how the educational material was presented.

Social behavior can also be studied through smartphone sensing. For instance, smartphone microphones can be used to detect the frequency and duration of conversation as a sociability measure (Wang et al. 2014). Chen et al. (2014) used Bluetooth signals as an indicator of social context, being able to classify real-world environments such as mall shopping and taking the subway. Texting and calling can also be analyzed to deduce social behavior (Schuwerk et al. 2019), including the Big Five personalities (Mønsted et al. 2018). Additionally, keystroke analysis has revealed differences in the semantic content of texts across various messaging platforms. For example, analyzing keyboard typing revealed a preference for sharing personal interests like books and music and discussing leisure activities on Facebook, while SMS communications were more focused on task-oriented exchanges (Liu et al. 2022).

Practical Considerations

Conducting in-the-Wild Smartphone Studies

Smartphone sensing studies can be conducted in several ways, although most studies typically follow a standard structure.

Firstly, researchers should decide on their study objectives, which can then inform the necessary sensor data to collect. Selecting a suitable range of sensors at the beginning of the study can help researchers decide which existing sensing app they should use, or if they should develop a new tool to better meet their needs. Other considerations include the length of the study and frequency of sampling, as well as the required device type. In-the-wild smartphone studies are generally longitudinal as it often requires a longer duration for behavioral patterns to be revealed, commonly lasting from a few days to several months. The specific study duration is dependent on the study objectives and the expected timeframe to observe significant behavioral changes or patterns. For example, a study aimed at understanding daily smartphone usage patterns may only require a few weeks of data collection, as these behaviors can be more quickly established. In contrast, a study examining the impact of a digital intervention on mental health might span several months to accurately measure changes over time. Additionally, the sampling frequency should be determined based on the type of data being collected and the research questions being addressed. For instance, studies focusing on physical activity might require more frequent sampling to capture detailed movements, whereas studies on app usage patterns might sample less frequently. Researchers should also decide whether participants are to use their own smartphones or if a standardized device is provided to all participants for the duration of the study. A primary benefit of participants using their own smartphones is that they do not need to switch to a new device, which can take time to adopt and may not be fully representative of a participant in their "natural" environment. In doing so, study results will have higher ecological validity (whether study findings can be generalized to real-world contexts) as participants are more familiar with using their own devices. Additionally, the use of participant-owned smartphones means that researchers do not need to supply, distribute, and retrieve their devices throughout the study, hence allowing for conducting fully remote studies. However, allowing participants to use their own smartphones will likely create additional data artifacts due to differences in device behavior. Even various phones running the Android OS can have different levels of performance, such as sampling rates, due to differences in sensor hardware used by different smartphone manufacturers. The lack of standardization also makes troubleshooting errors during the study more challenging and may introduce noise that is difficult to correct during data preprocessing. Therefore, despite the potential decrease in ecological validity, some studies provide participants with the same mobile devices to use throughout the study. However, this method is evidently more resource-consuming and less feasible for studies with larger samples.

After designing the study, participants can be recruited based on the studied population. Recruitment strategies should be tailored to the target demographic to ensure a representative sample. This might involve using various channels such as social media, university mailing lists, or partnerships with organizations that have access to the desired population. For example, recruitment for a study aiming to understand how mobile app usage related to academic productivity for university students could occur through campus-wide emails or student notice boards. Incentives such as gift cards or course credit can be particularly effective in this group. In a study focusing on older adults' use of health-related apps, researchers might collaborate with medical clinics or community groups to reach potential participants. In such cases, face-to-face recruitment methods may be more effective.

Following participant recruitment, an onboarding process is essential to ensure they understand the study's aims, what is expected of them, and how to use any required technology. For studies where participants are provided with a standard smartphone, this may include meeting with the researcher to receive the device and understand the study instructions, such as any tasks or questionnaires they need to complete. To improve the reliability of data transmission from the participant's smartphone to the researcher's database, participants may be asked to meet with the researcher periodically to upload their data directly from their phone. On the other hand, studies where participants use their own smartphones may be conducted fully remotely. Researchers can digitally provide instructions on how to install and configure the sensing app, such as downloading it from the app store or a hosting website, as well as any additional information including study duration and tasks. In both cases, participants should be provided with communication channels (e.g., email) for contacting the researchers during the study. Regular communication throughout the study can help maintain engagement and address any issues or concerns that arise. Monitoring the collected data in real time or frequently is equally important in identifying and rectifying any issues, such as technical errors in the sensing app or participant noncompliance with study protocols. In addition to these tasks, researchers should also be prepared to adapt their strategies as the study progresses. This might involve adjusting recruitment efforts if initial targets are not met, or modifying engagement tactics if dropout rates are higher than anticipated. As the study concludes, researchers should debrief participants and collect final feedback, which can provide valuable insights for future research. Participants may be given the option to be notified of publications arising from the study as an acknowledgement of their contributions.

Challenges and Potential Solutions

Conducting in-the-wild studies, particularly with smartphones, poses several challenges including addressing technological limitations, maintaining participant engagement, and ensuring data quality.

The design of the technology for smartphone sensing is critical in the success of in-the-wild studies. Smartphone sensing studies are commonly conducted through an app and integrated within a broader sensing system. Most sensing apps are comprised of a user interface, allowing participants to interact with components of the study such as disabling/enabling sensors and answering questionnaires. Many sensing apps offer data collection from a broad range of hardware and software sensors, and the selection of sensors can differ based on the type of study being conducted. Due to the large volume of data captured via passive sensing, sensor data is typically sent to a database that can store large datasets such as MySQL, or in the case of longitudinal studies conducted with many participants over a longer timeframe, databases designed for handling big data such as MongoDB may be preferred. Storing this captured data allows for the data to be analyzed in real time or after the conclusion of the study. For studies requiring real-time data analysis, such as those delivering in situ recommendations or interventions based on the user's context (e.g., providing music suggestions catered for the user's current physical activity), participant data must be transferred to the database immediately upon collection to maintain the integrity and timeliness of its analysis. In contrast, studies that do not require real-time analysis, such as those that aim to understand specific phenomena in an experimental setting (e.g., determining the effect of smartphone app usage on exam scores), may transfer batches of data to the database at given intervals. Because sending data to a remote database requires a network connection such as Wi-Fi and battery power, batching and sending all data collected at once for a given interval (e.g., every 30 minutes) can help to save resources. When designing databases for storing smartphone sensor data, it is important to consider the volume of data generated by various sensors at different sampling frequencies. These databases need to be scalable, efficient, and capable of handling potentially large influxes of data, especially in studies involving multiple participants over extended periods. Smartphone sensors can be categorized as high-, medium-, or low-frequency sensors, for example:

- Accelerometers are high frequency, generating substantial amounts of data, particularly at high sampling rates. For instance, at a sampling rate of 100 Hz (samples per second), with each sample comprising approximately 10 bytes, the data generated can amount to approximately 86 MB per day per device. This high-frequency data collection is essential for detailed motion analysis but requires significant storage space, especially in longitudinal studies with multiple participants.
- GPS sensors are medium frequency, typically generating less data compared to high-frequency sensors like accelerometers. By sampling every minute with each sample being around 10 bytes, the data can amount to about 0.01 MB per device per day. The actual data volume may vary depending on the nature of the study and the necessary tracking granularity.
- Battery sensors are low frequency, typically generating minimal data due to its event-based activation, such as when the battery level changes. Because this sensor is primarily used to record the current battery level and state (i.e., charging, not charging), the data recorded from each change is very small, often less than five bytes. Even with an average of 100 battery level changes per day, the daily data contribution would not exceed 500 bytes, making the battery sensor's data impact on storage negligible.

Therefore, researchers should compute an estimate of the required data storage based on the range of collect sensors, the number of participants, and study duration, while reserving additional storage to accommodate technical difficulties. Doing so can mitigate the issue of having insufficient storage while also avoiding consumption of excessive resources.

Most smartphone sensing apps are built for the Android or iOS operating systems, largely due to their popularity among consumers. Due to Apple's closed ecosystem and stricter control over app permissions, third-party apps on Android are generally able to capture information from a wider range of sensors than iOS. For example, Android systems allow for capturing which apps are being used or collecting screen contents using accessibility services, which are either impossible or much more difficult to replicate on iOS. However, the standardized and controlled nature of iOS devices results in a more uniform ecosystem, where there is less variability in sensor performance and data quality across devices, as well as offering tighter data security. Therefore, study designers should consider their study objectives and required functionalities when selecting their app platform.

Ensuring the quality and integrity of data in uncontrolled settings is a significant hurdle in conducting field studies. To address this, automated systems can be leveraged to identify inconsistencies or missing data, which can highlight potential issues with sensor functionality or participant compliance early on. This proactive approach enables timely adjustments to rectify errors and mitigate further issues, although this process can be cumbersome for researchers and may require a dedicated team for studies with large sample sizes. Additionally, analyzing the sensor data in real time can be used as a form of data monitoring, such as employing visualizations to display the collected data. Visual representations of participant compliance and data volume can provide immediate insights into the study's progress and highlight areas that may require intervention, such as increasing the database allowance to accommodate more data. Furthermore, researchers should establish protocols for responding to data anomalies. This may involve reaching out to participants for clarification, adjusting sensor settings, or recalibrating data collection parameters. Transparent communication with participants about these adjustments can help maintain their cooperation throughout the study while improving the quality of collected data.

Keeping participants actively involved and compliant is crucial for the success of any study, particularly those conducted in naturalistic settings where researcher control is limited. High dropout rates or declining participation can compromise the representativeness and reliability of the collected data, ultimately affecting the study's outcomes and conclusions. To mitigate these risks, researchers should employ strategies that enhance participant engagement and motivation. This can include clear and ongoing communication about the study's purpose, progress, and the importance of each participant's contribution. Personalized interactions, such as study updates and responsive support for any issues participants encounter, can foster a sense of involvement and commitment. Incentivization is another effective tool for maintaining engagement. This can include rewards such as gift cards or the chance to win prizes in a lottery. The type and value of incentives should be carefully considered to ensure they are proportionate to the amount of effort and time required, and relevant for the target population. Additionally, designing a user-friendly and minimally intrusive data collection process can help reduce participant burden and prevent dropout. This might involve optimizing app interfaces for ease of use, minimizing the frequency of active inputs required from participants, and ensuring that the data collection runs unobtrusively in the background of participants' daily lives. Furthermore, post-study engagement such as providing participants with summaries of the study findings and acknowledging their contribution to scientific knowledge can enhance satisfaction and willingness to participate in future research. This approach not only benefits the current study but also builds a positive relationship between participants and the research team for future research opportunities.

Ethical Considerations

Carrying out smartphone research in real-world settings involves numerous ethical considerations that require careful planning and implementation at all stages of the study (Petrie 2024).

Informed consent is a fundamental ethical requirement in research involving human participants. It is particularly important in smartphone-based research due to the possibilities of revealing individual user information through smartphone data. Participants must be thoroughly informed about the nature of the data being collected, its intended use, and any potential risks involved. They should also be provided clear, understandable, and accessible information about the study to help them make informed decisions about their involvement. This is particularly relevant in the context of using smartphone data for psychometric evaluations, where individuals should be made aware from the onset of the possibility that their digital footprint could be analyzed. As part of this informed consent process, participants could either give advanced consent for periodic psychometric analyses of their data, or a dynamic consent model could be employed, requiring their approval each time their data is to be used for a new assessment (Tauginienė et al. 2021). This dual-layered consent approach not only informs participants about the data collection and its intended use but also empowers them with the autonomy to decide on how their data is used at different stages of analysis, ensuring their participation is both knowledgeable and voluntary.

Gathering data through smartphone usage raises privacy implications, especially due to the personal nature of the data collected. It is essential that individuals participating in smartphone sensing studies have full autonomy over their digital information to maintain their privacy rights. Researchers should provide straightforward options for participants to opt out of the study or to request the deletion of their data at any stage. For example, a participant could easily exit the study by deleting the research application from their device, preventing any further data collection from their smartphone. They should have the right to request their information be removed from the researchers' database without explanation at any point during and after the conclusion of the study. Participants may also request to see their data during the study to review and understand the extent of information gathered about them. These measures ensure that participants can manage their involvement and their data with minimal hassle.

When conducting passive smartphone sensing, participants should be asked to give permission for activating various phone sensors and be notified of ongoing data capture (Boonstra et al. 2018), which can be facilitated through the smartphone itself. To increase autonomy and privacy in mobile sensing, sensing platforms should provide control to users over what data they choose to share (Bemmann et al. 2022). For example, participants can be given in-app control over enabling and disabling sensors (Xiong et al. 2016), such that they can disable any sensors they feel uncomfortable with and re-enable them if they choose to in the future. This flexibility not only empowers participants with greater control over their privacy but also introduces a valuable source of behavioral data. The decision-making process behind disabling and re-enabling sensors can provide information about participants' preferences and comfort during the study. For instance, frequent toggling of sensors could indicate situational privacy needs, providing researchers with insights into how participants interact with their smartphones and perceive their own data privacy when they are performing different tasks. Additionally, patterns in sensor usage can inform the design of future studies and sensing technologies. Understanding which sensors are more frequently disabled could guide researchers in understanding which are more privacy-sensitive and help in designing less intrusive studies. Incorporating user feedback can further enhance this dynamic. By allowing participants to provide reasons for disabling sensors, researchers can gain direct insights into user concerns and preferences. This feedback loop not only enriches the data collected but also fosters a more participatory research environment. Ultimately, the ability for participants to control sensor settings goes beyond mere privacy protection, becoming a source of rich behavioral data that can enhance the understanding of how people interact with different sensors on their smartphones.

Data security is a critical aspect of smartphone sensing studies, particularly given the personal nature of the data collected. Smartphone sensing data should be handled securely at all stages within the study, including during data capture, storage, and dissemination. Secure data collection can be facilitated through the use of smartphone apps that encrypt sensor data during transmission, for instance, by employing secure sockets layer (SSL) over SHA-256 RSA encryption when uploading data (van Berkel et al. 2022). For data storage, protected databases should be implemented and accessible only to key members of the research team, and regular checks should be undertaken to ensure that security is being maintained. Data sharing must be conducted in adherence to stated ethics guidelines, including ensuring participant understanding of who the data will be shared with. Anonymization should also be applied to the data to increase data security. Given the potential for certain sensor data such as location and keystrokes to directly identify individuals, researchers must employ techniques to anonymize this information, possibly substituting identifiers such as names, email addresses, and phone numbers with placeholders, or even removing them entirely.

Summary and Future Directions

This chapter provides a survey of the evolving field of smartphone sensing, highlighting the diverse array of sensors embedded in modern smartphones and their applications in capturing in-the-wild user behavior. By detailing the functionalities and potential uses of different sensor types, the chapter presents the richness of data that smartphones can offer for understanding human behavior in natural settings. An overview of how to conduct in-the-wild smartphone studies is provided alongside practical considerations such as the balance between passive and active sensing. The chapter highlights the importance of data preparation and analysis, which are crucial for transforming the vast amounts of raw sensor data into meaningful insights that can inform various domains such as health, education, and social behavior. Challenges related to data quality, participant engagement, and technological constraints have been addressed, with recommendations provided for mitigating their effects. Ethical considerations, especially concerning privacy, informed consent, and data security, have been emphasized to highlight the imperative of upholding ethical standards in smartphone-based research.

Moving forward, key areas for future research in smartphone sensing include developing more refined data collection and analysis methodologies. An area of focus is the enhancement of ground truth data collection techniques that can enhance the accuracy and reliability of insights derived from sensor data. This could involve the development of novel techniques for capturing and interpreting user behavior through smartphones, potentially as an improvement to existing methods such as screen text sensing and screenomes. As smartphone sensing capabilities advance, ethical considerations must continue to be maintained. Ensuring the privacy and security of participants' data, as well as preserving transparency and consent throughout the research process, will remain paramount. Furthermore, the application of cutting-edge technologies such as generative artificial intelligence opens new pathways for the analysis and understanding of sensor data. These technologies can potentially uncover deeper, more nuanced patterns in user behavior that are not readily apparent through traditional analytical methods, creating a significant avenue for exploration.

Beyond smartphones, other wearable devices, such as smart watches, offer additional avenues for capturing and understanding in-the-wild human behavior. Like smartphones, these wearable devices contain various sensors, such as accelerometers, heart rate monitors, and GPS. These sensors can unobtrusively capture continuous, real-time data on physical activity, physiological states, and environmental contexts. The ability to seamlessly integrate data from both smartphones and wearables allows researchers to capture a more holistic view of an individual's daily life, combining insights from their physical environment, such as location and physiological signals, with digital behaviors, such as smartphone usage patterns and interactions. Smart watches, for instance, can be particularly valuable for studying health-related behaviors, such as physical activity, sleep patterns, and stress levels, while remaining minimally intrusive. The combination of these technologies provides an enhanced understanding of both the physical and digital aspects of human behavior. As wearable technology continues to evolve, the potential for multi-device sensing will further expand the capacity for in-depth, longitudinal studies on human behavior.

Smartphone sensing presents a fertile ground for research, offering unprecedented opportunities to study human behavior in its natural context. By addressing current challenges and embracing future technological advancements, the field is set to make continued contributions to our understanding of the interplay between humans and their digital devices.

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