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A Systematic Review of the Event-Driven Activities in Social Applications

Ahmed A. Mostfa [1,], **Dhafer Sabah Yaseen [2]**, **Abdel-Nasser Sharkawy [3,]**
(ORCID: [1]0000-0001-8722-5306 and [3]0000-0001-9733-221X)

Abstract The ubiquity of phones and their compatibilities provides a good opportunity to use them as lifelogging information devices. The tracking usage application helps to mitigate the widespread use of social media on smartphones. Tracking apps can be used to monitor and limit social media and smartphone use, which can ultimately reduce the negative effects of phenomena of fear of missing out (FOMO) and social media engagement on smartphone addiction and distraction. In this paper, a structural review for tracking social applications in smartphones is presented. Many commercial force stop applications are not use for recording but are also for analyzing the experienced samples in which it entered by the users and their behaviors. To address these challenges, previous research works are investigated from the user application activities and their event-driven activities are analyzed. In addition, the tracking applications are divided into three categories and our third-party application is highlighted that tracks the frequency of use and time stamp and suggests temporarily blocking any applications that are overused. Some recommendations for future work are provided at the end of the paper.

Keywords: Systematic Review; Tracking Applications; Event Driven Activities; Smartphone Addiction; Mobile Sensing; Time Usage.

1 Introduction

The evolution and wide uses of internet-based technologies provide a challenge to parents navigating the media content. Prior research indicates that US parents have long believed that access to the facility with computers and internet use are important for children's academic success and future employability, [1], [2]. However, parents often lack the knowledge or resources to help their children acquire such skills, [2]. Thus, parents may be uncertain about how to effectively limit their children's internet use and protect them from inappropriate content or activities, [3]. This may involve setting clear rules and boundaries around internet and smartphone usage, using parental controls and filters to block inappropriate content.

Additionally, parents may also benefit from seeking out resources and support from schools, community organizations, and online networks [4]. Parents can help their children make the most of the opportunities offered by the smartphones while also ensuring their safety and well-being [5], [6]. Research has shown that excessive screen time on social applications could have negative impacts on youth's physical and mental health [7]. Extending such research, we expect the increase in smartphone use would result in increased levels of some types of psychopathologies.

Parental monitoring can include restrictions on when and how teens are allowed to use smartphones. Such events include limiting the amount of time they can spend online and monitoring which application they visit. It can also include monitoring computer activities, such as checking the browser history and any emails or instant messages sent. The major problem in parental control is to use the appropriate social tracking application that collects the necessary data for assessment. Where the applications findings could be different based on their methodology and purposes of use.

It cannot be relied on questionnaires as a based assessment method of social media use and addiction. Technological advancement discovers a new role of

Received: 04 May 2023/Accepted: 03 June 2023
Corresponding Authors
E-mails: [1]mostfa@uohamdaniya.edu.iq and [3]eng.abdelnassersharkawy@gmail.com
1 and 2 University of Al Hamdaniya, Department of Computer Science, Mosul, Iraq
3 Mechanical Engineering Department (Mechatronics Division), Faculty of Engineering, South Valley University, Qena 83523, Egypt.

tracking social usage. However, it can take different forms of collecting method tools. Such as, an application logs a file analysis to assess application's uses, or a third-party application. In which, it can work in the background to provide daily usage behavior. Therefore, we should simulate the questionnaires (social media use and frequency of usage) in the form of mobile application platform that has the previous capabilities. More often, questionnaires answer the question on the frequency of use (such as never at all times, two days per week, or absolute time frame) a user could engage? While the duration could answer the question how long, did a user peruse the social applications? The questionnaires have a long period to observe the ground truth and answer these questions. Ultimately, it is still biased method due to social desirability.

Moreover, users may neglect their healthy lifestyle. Such as poor sleep, hygiene, and prolonged social isolation. We believe that there should be adequate tools for self-management of overall wellbeing and health, [8].

There are applications that collect event driven activities such as space-time information and phone locked- unlocked for the purpose of parental control and regulation purposes. These apps are designed to monitor the user's activities on their smartphones and ensure their safety. A few examples of such an application are Norton Family. The application allows parents to monitor their children's smartphone activities, including calls, texts, and web browsing. It also tracks the child's location and sends alerts to parents when the child enters or leaves specific areas. Moreover, Kaspersky Safe Kids allows parents to set limits on their children's smartphone usage, including screen time limits and app usage restrictions. It also provides real-time location tracking and alerts when the child enters or leaves designated areas. Lastly, Qustodio allows monitoring the user's smartphone activities, including social media usage, and messaging apps. It also provides location tracking and set usage limits on individual apps.

The after-mentioned applications are based on intervention solutions, not for assessment purposes or to capture a user's behavior for research analysis. The Android platform can be utilized to design a mobile tracking system with a connected web application and hosting server. The developed Android application would then collect the data about the user's location, the event-driven activities, and send that data to the web for storage and analysis. The web application could provide a graphical interface to view the collected data, as well as provide tools for analyzing the data and creating reports. Additionally, the Android application could provide tools to manage user access, set up alerts notifications, and configure the settings of the tracking system due to open access libraries, as we will discuss later in this paper.

The main contribution of this paper is to review the structural tracking of social applications in smartphones by presenting the most significant applications by classifying them in different categories based on their use. In addition, a lot of previous research on user application behaviors and methodology used has been discussed. We also highlight our previously published application in comparison with a different study and suggest a future strategic work. This review is about practical research of work and very important for researchers who investigate/study the social applications usage in smartphones.

The outline of the rest of this paper is presented as follows: Section 2 shows the literature review influence of the social applications and Section 3 presents the method studies and discussions. Section 4 summarizes the main important points in the paper and gives some recommendations for the future.

2 Literature Review

This section investigates some previous research works that show the influence of social applications and their structural point of view.

Table 1. The stages that were used by Lin, J. et al. [8] to process the dataset on the smartphone.

Steps	Strategy		
First process	Classify the inferences of the end-user behavior and extract their features. Naive Bayes classifier based on a multi-variate Gaussian Model		
Second process	Transfer the events-driven activities made by the classification model to cloud infrastructure		
Third process	BeWell Mobile Portal allows the user to track their current and historical wellbeing scores and view their behavioral patterns.		
	Sleep frequency and duration of phone recharging events	*Social Interaction* Classifying (voice, non-voicing) audio segments.	*Physical activities* Driving, stationary, running, walking, etc.

Lin, J. et al. [8] discussed the BeWell application which describes the design and implementation of BeWell, a smartphone application that aims to promote wellbeing by encouraging repeated use through personalized feedback, social comparison, and game-like elements. The influential of study tried to answer the question about the links between behavior and wellbeing by introducing the BeWell application. The application has processed the data in phases as shown in Table 1 and Figure 1 below.

Fig. 1. The BeWell application in animated aquatic ecosystem with three different graphical animals that represent different event activity (sleep, physical activity, and social interaction), [8].

The BeWell application passed the experimental implementation by benchmarking the resource consumption (such as battery and CPU usage) and validated its accuracy on five persons.

A better method of collecting and analyzing the dataset usage (such as timestamp, repetition of use, and usage behaviors in smartphones) is utilizing an open-source sensing and developing data processing platform. The MIT Media Lab. developed Funf platform. Funf was designed to collect, analyze, and manage various types of mobile sensor data, including accelerometer, GPS, Bluetooth, Wi-Fi, and others, from Android smartphones, [9]. As shown in Fig. 2, the framework provides a set of pre-defined sensors and data sources. Developers can easily customize these sensors or create new ones to suit their specific research needs. In which, Funf uses to collect objective data like screen time, checking frequency, and other usages.

Fig. 2. A snipping of the Funf framework, [9]. It shows the sensors on an Android device that can collect data, such as the GPS sensor, the accelerometer, or the microphone. The data collected is stored in a local memory or on a server. The Funf framework supports a variety of data storage options, including SQLite, CouchDB, and Amazon.

A researcher needs to download the Funf source code from the official GitHub repository of Funf. In which he/she can deploy the custom Android application by sharing it with participants through email, file-sharing platforms, or by publishing it on a public app store. Participants can then download and install the application on their smartphones.

Rawassizadeh et al. [10] presented a mobile phone-based life-logging framework called UbiqLog. In which, sensors were the core components of a life-log user activities. The on-device sensors continuously sensed the contextual information and provided crucial feedback. UbiqLog was designed to collect data by sensing and recording, not to reflect it to the user. The UbiqLog framework uses sensors that form the context data acquisition such as location, accelerometer, temperature, Bluetooth, and orientation. This raw data would then be aggregated in one meaningful dataset format. Figure 3 describes the architecture of the UbiqLog.

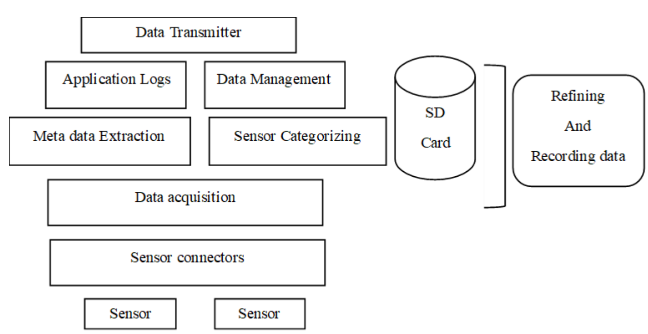

Fig. 3. The UbiqLog system architecture phases, [10].

The dataset would then move to the refining and recording phase. This phase consists of data aggregator, metadata extraction, and network transmitting. The data aggregator stores the events driven by the sensor on the SD card of the phone. The framework is generic and can be used for different cases and configurations. In addition, it is designed to be modular and extensible, allowing new sensors and data sources to be added easily. However, a few researchers could apply holistic approaches to track social activities and analyze their data logs without force stop their applications which we will discuss in the rest of the paper. As event-driven activities become increasingly important, a part of this study aims to highlight the app features monitoring. We are summarizing some of the smartphone applications. In which, they can track and monitor the user's behaviors, as presented in Table 2.

Table 2. The different event activities that each app is capturing.

Application available online	Screen logs (on/off)	Calls logs (in/out)	App launches	Timestamp duration
Instant	Yes	No	No	No
App Usage Tracker	Yes	Yes	Yes	Yes
Callyzer	No	Yes	No	Yes
StayFree – Screen time	No	No	Yes	Yes

3 Social Applications Study and Investigation

In this section, we discuss and analyze the different algorithms that were used by previous researchers for collecting and handling the dataset. Furthermore, we seek and try to find out the answers on what method was used by the researcher to obtain the data (i.e., classical survey questionnaire, a developed designed application that runs in the background, or screen time that build in the operating system). In addition, their results are discussed.

Althoff, T. et al. [11] explored the influence of the popular social game Pokémon Go on physical activity by analyzing data from a large sample of players. The authors found that the game had a significant positive effect on physical activity and that repeated use of the application was associated with higher levels of physical activity. Mäntymäki et al. [12] examined the repeated use of social virtual worlds, which are a type of social application that allows users to interact with each other in a simulated environment. The authors conducted a survey and interviews with users of social virtual worlds to explore the gratifications they derived from using the applications and the social norms that emerged from their use. The results suggest that social virtual worlds can provide a variety of gratifications, including socialization, entertainment, and self-expression, and that users develop social norms around issues like etiquette, privacy, and trust. F.-C. Chang et al. [13] discussed several major problems related to children's use of mobile devices and smartphones in Taiwan. These include:

1) The issue of smartphone addiction among children in Taiwan and its negative effects on children's mental and physical health, academic performance, and social development.
2) Excessive screen time: The authors noted that many children in Taiwan spend a significant amount of time on their smartphones and other mobile devices, leading to concerns about the negative impact on their physical and mental health, as well as their academic performance.
3) Cyberbullying, which has become more prevalent with the increasing use of social media and messaging apps among children.

Lack of parental mediation: Many parents are not actively involved in mediating their children's use of mobile devices and smartphones, which can lead to increased risks such as exposure to inappropriate content, cyberbullying, and excessive screen time.

F.-C. Chang et al. [13] used a self-report questionnaire to a sample of 997 children aged 9-18 years old, and their parents or guardians. The questionnaire consisted of several sections, including demographic information, smartphone use patterns, smartphone addiction, and parental mediation practices. The authors used statistical analyses, including descriptive statistics, correlation analyses, and regression analyses, to analyze the survey data and examine the relationships between children's smartphone use, parental mediation practices, and smartphone addiction.

Moreno, M. A. [14] examined the relationship between time spent on social media and mental health indicators in a cohort of Australian youth. The study found that higher levels of time spent on social media were associated with increased levels of anxiety and depression, and decreased levels of self-esteem. The study involved 1,478 Australian youth aged between 14-24 years. The sample was recruited through an online research panel. Participants completed an online survey which included questions on time spent on social media (using a modified version of the Pew Internet and American Life Project's Social Networking Survey), as well as measures of mental health indicators including anxiety, depression, and self-esteem (using standardized scales such as the Generalized Anxiety Disorder 7-item scale and the Rosenberg Self-Esteem

Scale). The authors used multivariate regression analysis to examine the relationship between time spent on social media and mental health indicators, controlling for potential confounding variables such as age, gender, and socio-economic status. However, this study relied on self-reported measures, which may be subject to bias. Additionally, the study was cross-sectional, which limits the ability to draw causal conclusions.

J.A. Wright et al. [15] developed a mobile application specifically for the purpose of tracking social media use. The app was called "Social Media TRACKER" and it was designed to be installed on participants' smartphones. The app collected data on participants' social media use including the type of social media platform used, the time spent on each platform, and the number of posts and interactions, where the data stored on the participant's phone. The application was developed using an open-source platform called CommCare, which is designed for creating and deploying mobile applications for health research and interventions. As such, it has several limitations that should be considered when interpreting its findings:

1) Small sample size: The feasibility study included only 10 participants.
2) Self-selection bias: Participants who volunteered for the study may have been more interested in tracking their social media use than those who declined to participate.
3) Limited focus on health outcomes: The paper did not report on any health outcomes associated with social media use.
4) The dataset stored on the user’s phone, which was not useful for research analysis by the researchers unless the user shares its own data.

The paper by Nathan Eagle and Alex Pentland [16], developed a mobile application collecting the data from a custom software application called "Reality Mining” installed on the mobile phones of 100 students at the Massachusetts Institute of Technology (MIT) in the United States. The software collected a variety of data, including:

1) Call and SMS logs: The software recorded the time and duration of each phone call and SMS message sent or received by the participants.
2) Bluetooth proximity: The software detected when two phones were close to each other (within 10 meters) via Bluetooth signals.
3) Location: The software used GPS to track the location of each phone at regular intervals.
4) Accelerometer and microphone data: The software recorded data from the phone's accelerometer and microphone to detect when the phone was in use and whether it was being carried or left stationary.

The data collected by the software was used to analyze patterns of social behavior, communication, and mobility among the participants. The study aimed to gain insights into how social networks change over time and how people interact in different contexts. The dataset used in the study was collected over the course of one academic year, from September 2004 to June 2005. However, the outcome results found that social networks among the participants were highly dynamic and could change rapidly over time. Participants added and removed contacts from their network frequently. The authors also found that participants' mobility patterns were correlated with their social behavior and interactions. Where the limitation could conclude with the limited geographic scope (MIT campus). Also, the study was conducted over the course of a year, which may not capture longer-term changes in social networks and behavior.

McDuff, D. et al. [17] described the development of a custom software application for collecting social data from users' smartphones. The application, called MoodScope, collected data on users' smartphone usage patterns, including information on which applications were being used, how long they were being used for, and the time of day at which they were being used, as presented in Table 3. The authors used machine learning algorithms to analyze this data and to infer users' moods based on their smartphone usage patterns. The collected data on the following types of events were as follows:

1) Screen unlocks: When the user unlocked their smartphone's screen.
2) Applications launched: When the user launches a new application.
3) Phone calls: When the user made or received a phone call.
4) Text messages: When the user sends or receives a text message.

The application was designed to run in the background of the user's smartphone and collect data on these events as they occurred. The collected data was then sent to a server for analysis. However, the study was conducted on a relatively small sample size of 32 participants. Furthermore, the study only measured participants' moods over a one-week period, which may not be long enough to capture the full range of variation in mood over time. However, the approach of collecting the data from smartphone varies from project to other and it needs partitioning the data into segmentation activities for regulation and analysis. Therefore, a transportation application presented as a model in smartphone by Tae [18]. The study outcome gave a high accuracy classification transportation mode (walking, biking, and driving) using smartphone (Accelerometer, GPS, and WiFi). Once the data segmented into distinct activities (as illustrated in Fig. 4), it was used as inputs to the Random Forest Classifier. This classifier is trained to predict the transportation mode of each activity segment (such as, Walk start detection, Walking stop detection, and Vehicle riding detection).

Table 3. The dataset usage from the MoodScope application, in the study of McDuff, D. et al. [17].

Data Type	Histogram by	Dimensions
Email contacts	#Messages	10
	#Characters	10
SMS contacts	#Messages	10
	#Characters	10
Phone call contacts	#Calls	10
	Call Duration	10
Website domains	#Visits	10
Locations Clusters	#Visits	10
Apps	#App launches	10
	App Duration	10
Categories of Apps	#App launches	12
	App Duration	12
Previous 2 Pleasure and Activeness Averages	N/A	4

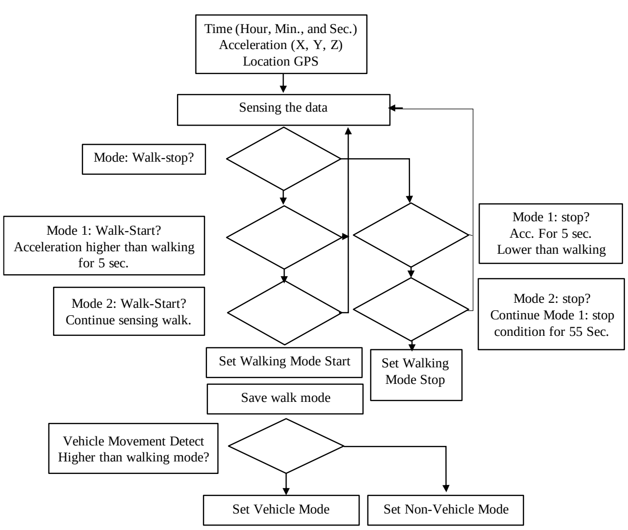

Fig. 4. The algorithm of extraction walking and riding features from a custom data logging application by Tae, [18].

Although the author achieved high accuracy in detecting transportation mode using smartphone, the Random Forest classifier is considered a complex algorithm to extract the features of moving mode. Therefore, our recommendation is to use a more custom open sensing and data processing platform (described in the Conclusion and Recommendations section).

Our previously published work (Mostfa et al. [19]) investigated the time spent and the repetition of using the Social Network Sites (SNS) in Android applications. The approach, they sought to raise the awareness and limit the repeated uses of SNS, by introducing AndroidTrack app. AndroidTrack was designed to monitor and apply valid experimental studies to improve the impacts of social media on Iraqi users. Data generated from the app updated periodically at Google Firebase Real-time Database. We profiled data log from 19 users along with their application name packages. Each user showed different application uses and time-frequency of usage. The data lifecycle went with two stages. First, the mobile data log traffic was stored at the SQLite database. Secondly, the stored data would be sent to Google Firebase real-time database. Where the data is structured in a JSON format and finalized for statistical analysis. The Factor Analysis algorithm is utilized to find the linear relationship or multicollinearity between the factors, as shown in Table 4.

Table 4. The factor analysis for the applications in terms of number of usage (frequency of use) along with their saturations (correlation coefficient), Mostfa et al. [19].

Factor	Application before rotation	Saturation	Application after rotation	Saturation
1	Viber	-1	Viber	-0.961
2	Google play store	-0.958	YouTube	-0.768
3	Tiktok	-0.807	Telegram	-0.879
4	Snapchat	-0.825	Facebook	-0.884
5	Facebook	-0.692	Camera	0.969
6	Messenger	-0.516	Snapchat	-0.986
7	Tiktok	-0.530	Messenger	-0.720

These measures deduced that a user engaged in whilst on their smartphone can be beneficial to distinguish between what application is a real problematic and what application is required to use. In addition, the conclusion was that the interests in measuring smartphone use were more accurately and objectively by apps rather than the classic surveys. Smartphone tracking can be a useful tool for observing smartphone use and reactivity effects in using this method.

In Toth, R. [20], the study was like what Mostfa et al. [19] implemented. The author collected data on participants' smartphone usage patterns and reactivity to notifications using tracking software. To measure the parameters of days, frequency, and duration of smartphone usage, the author used data from the tracking software that was recorded in JSON (JavaScript Object Notation) format. The application collected the data based on the event driven activities such as (activity paused, activity resumed, keyguard shown, and device shutdown), as shown in Table 5. The procedure followed by ATT involved accessing the log file in the Android operating system to track and categorize events related to smartphone use. The data collected by ATT provided insights into changes in smartphone use patterns and attitudes towards smartphone use. The study had several limitations, including a small sample size, lack of control for external influencing factors. However, there is a range of methods for collecting passive objective measures, such as screen time, app usage, and GPS data. These measures can be collected through a variety of sources, including built-in functions of the smartphone operating system, third-party apps, and wearable devices, Ryding et al. [21].

Table 6 summarizes the previous research works with applications that had the functionality to monitor the usage time spent on smartphones studied the tracking social applications.

Table 5. The events driven from the participants' smartphone group, in the study of Toth, R. [20].

Event type	Description
1	Activity resumed
2	Activity paused
17	Keyguard shown
18	Keyguard hidden
26	Device shutdown
27	Device booted

Table 6. A comparison of tracking social applications in smartphones and assessing their usage patterns.

Researchers	Application	Usability	Methodology
Rouvoy, R., & Seinturier, L. [22]	MyTracks	1) Fitness enthusiasts 2) Location-based service providers	Track and record a user's location using GPS data.
Wolf, L. et al. [23]	EasyTracker	For researchers and transportation planning	Phone's sensors and GPS.
Toth, R. [20]	A Tricky Tracker (ATT)	Tracking user's activity. (Screen time, frequency of use, and duration).	Extract phone system logs (Jason file format) for data collection and event driven.
Van Ballegooijen, W. et al. [24]	MoodMonitor	To assess the reactivity of individuals to ecological momentary assessment (EMA) of depressive symptoms.	Complete the EMA assessments of their mood, energy level, and cognitive functioning using the MoodMonitor application questionnaire notifications.
Elhai, et al. [25]	'Moment' apps	Investigate smartphone usage among college students and mobile usage behaviors (such as incoming and outgoing calls, or time spent on apps).	The author used online survey that included demographic questions, measures of depression and emotion regulation as well as asked participants to install the Moment on their iPhone which recorded the frequency and duration of smartphone use, the number of unlocks per day, and the duration of each session of use
Tossell, et al. [26]	'LiveLAb' app	Investigate smartphone addiction use.	Collects the data on various smartphone usage behaviors, including the number of times the phone was unlocked, the duration of use, the type of application used, and the time of day of use.

4 Conclusion and Recommendations

The phenomena of fear of missing out (FOMO) the social events and engagement became an important role in smartphone addiction and distraction. The tracking usage application helps to mitigate the widespread use of social media on smartphones. Tracking apps can used to monitor and limit social media and smartphone use, which can ultimately reduce the negative effects of FOMO and social media engagement on smartphone addiction and distraction, Vempati [27]. Although it is expensive and time-consuming, and requires advanced programming skills and systems architecture knowledge, it is necessary to custom-build every life-logging application running on smartphones. Such as behavior learning and health monitoring.

As we concluded by categorizing the use of measures that do not rely on self-report or subjective assessments in mobile usage as follows:

1) Collection of data on various aspects of smartphone use (application can run in background): Examples such as frequency and duration of phone usage, screen time, the number of times the phone is unlocked, and other usage behaviors.
2) Third-party application: An example is to collect data on the type and frequency of apps used on the phone. Such as the number of times an app accessed, the duration of use, and the time of day of use.
3) The screen timing in smartphones has built-in screen time tracking features that automatically collect data. Such as Apple's Screen Time feature or Google's Digital Wellbeing feature.

However, in the previous studies, we could not find which valid application could really be used to eliminate the repeated uses of social network applications. We want to highlight the important role that parental monitoring can play in shaping adolescent internet use and underscore the potential benefits of increased parental involvement in this area. Therefore, in future work, it recommended customizing previous work presented by Mostfa et al. [19] to adopt the algorithm to force-stop social media apps after a period, as shown in Fig. 5.

Where parents can set time usage limitations for each application while the user is sniffing. The time usage (i.e., time spend) on social media is considered a crucial variable in assessing smartphone addiction and behaviors. Based on our studies, the average time spent is between four to eight hours per day. Moreover, lowering the time per interaction can be done by measuring the duration of spending per number of launches. However, the main goal is to emphasize the standardized baseline to distinguish the problematic usage behaviors and addictions, by utilizing predefined set time limits (as described in Fig. 5) to be considered as a measure of research.

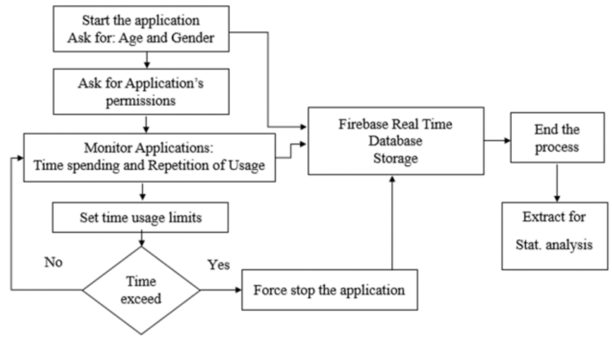

Fig. 5. The flowchart of setting up time usage to limit the frequency of uses in the AndroidTrack application, [19].

These measures have inferred that the activities undertaken by a user on their smartphone can be advantageous in discerning the genuineness of a problematic application and the indispensability of a required application. Furthermore, the conclusion reached was that the pursuit of quantifying smartphone usage is more precise and impartial when conducted through applications as opposed to traditional surveys. Smartphone tracking emerges as a valuable instrument for observing smartphone utilization and gauging the impact of reactivity through this methodology.

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