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Stanford Screenomics: An Open-source Platform for Unobtrusive Multimodal Digital Trace Data Collection from Android Smartphones

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Competing Interest: None.
Keywords: digital trace data, digital medicine, digital health, mobile health data
Word Count: 8319
Date of Submission: [06] 2025
This article has not been published before and is not currently being considered for publication.

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DECLARATIONS

Funding: Research reported in this publication was supported in part by the National Heart, Lung, And Blood Institutes of National Institutes of Health under Award Number R01 HL169601. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institute of Health.

Conflicts of interest/Competing interests: The authors declare that there are no competing interests related to this work. There are no financial, personal, or professional relationships that could be perceived as potential conflicts of interest.

Ethics approval: Not applicable.

Consent to participate: Not applicable.

Consent for publication: All authors have reviewed the final manuscript and consent to its publication.

Availability of data and materials: The text-based, illustrative 24-hour digital trace data collected using the Stanford Screenomics platform is available from the corresponding author upon request. The original screenshot are not available, as they have not been processed to protect the privacy of individuals whose information was captured.

Code availability: The source code for the Stanford Screenomics platform developed by I.K. and J.B. is available for public access at: https://github.com/iansulin/stanford_screenomics

Authors' contribution: I.K. conceived and designed the work, conducted data acquisition and analysis, interpreted data, drafted the manuscript, and performed critical revisions. I.K. and J.B. developed the software, with N.K. assisting in its testing. M.C. contributed to the conception and design of the work. D.E.C. contributed to data interpretation and critical revisions. N.H., T.N.R., B.R., and N.R. contributed to the conception and design, data interpretation, critical revisions, and secured funding. All authors reviewed and approved the final manuscript.

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ABSTRACT

Smartphone-based digital trace data can offer powerful insights for identifying behavioral patterns and health risks. However, existing tools for comprehensive data collection lack scalability, customizability, transparency, and accessibility. To address these gaps, we developed an open-source platform that enables in-situ capture of multimodal digital traces from smartphones (e.g., moment-by-moment capture of screenshots, application usage logs, interaction histories, and phone sensor readings). The Stanford Screenomics Data Collection application allows researchers to tailor data types and quality, data transfer methods, and upload cadence. The Dashboard application supports real-time monitoring of participants' data provision, identification of data issues, and automated reactive communications to participants. The platform's back-end employs a NoSQL database for secure, and HIPAA-compliant storage. Using illustrative 24-hour digital trace data we demonstrate how the platform expands the range of possible digital phenotyping studies.

[132 words]

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INTRODUCTION

The digital context has emerged as a new social ecology, engaging large segments of the population for extended periods (Navarro & Tudge, 2023). However, understanding this digital ecology has been challenging, as traditional measures have been limited by relatively coarse time-based metrics. The recent rise in the collection of digital traces, defined as records of activity from online systems, has opened new avenues for researchers and clinicians to investigate a diverse collection of social phenomena. The breadth of possible applications of digital traces is impressive and includes, for example, adolescent mental health (Jensen et al., 2019; Orben & Przybylski, 2019), behavioral health trends (Amir et al., 2019; Kim et al., 2023), political orientations Chan et al., 2017; Kosinski et al., 2013), the development of interpersonal relationships (Allen et al., 2014; Pentland, 2014), online purchases (Audy Martínek et al., 2023; Kunst & Vatrapu, 2019) and education and learning (Du et al., 2023; Lämsä et al., 2025). These different theoretical areas all have in common the desirability of obtaining granular records of digital experiences, often critical experiences that occur within seconds, that allow researchers to theorize about short time domains that have heretofore been invisible but are important for studying human behavior.

Digital trace data relevant to these research areas come from various sources, including individuals' smartphones, wearable devices, and laptops. Among those, smartphone-based digital traces have become particularly useful due to the widespread adoption of smartphones, and the ability to capture fine-grained, objective, and continuous data about an individual's physical, cognitive and social behaviors, and their environments. This provides researchers and clinicians with a detailed, unobtrusive, and scalable window into a plethora of real-world human activities. Consequently, smartphone-based digital traces enable large-scale, cost-effective studies and population-level analyses, yielding unprecedented insights into human behavior and health (Eagle & Pentland, 2006; Gordon & Mendes, 2021; Lathia et al., 2017; K. Lee et al., 2023; Ohme et al., 2024). Notable examples include nationwide research on contact tracing, mobility trends, and behavioral shifts during COVID-19—such as changes in

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physical activity, screen time, and call and text logs—informing health policies and strategies (Kleinman & Merkel, 2020; Mejova, 2022).

Early smartphone-based digital traces focused on basic usage information, such as call logs and SMS metadata. Over time, the scope of digital traces expanded to include location and activity data from built-in sensors like GPS, accelerometers and gyroscopes, as well as app usage and total screen time. However, much of this data remains limited to measuring the quantity of smartphone use and behavioral metrics, often serving as "digital exhaust" that provides indirect insights rather than a direct view of users' real experiences with their smartphones. The literature on the impacts of indirect monitoring on smartphone use on health and behavior has been mixed (Twenge, 2017; Amez & Baert, 2020; Nam & Cha, 2024; Singh & Samah, 2018), we believe because sensor metrics and usage logs alone do not provide information about the content actually experienced on smartphone screens. Many research questions remain unexplored simply because we lack information on what users are actually seeing and doing on their screens (Faust et al., 2024; Ohme et al., 2024; Ram et al., 2020; Reeves et al., 2021; Yee et al., 2023).

A promising method to bridge this gap is capturing content-based measures, such as smartphone screenshots and user-smartphone interaction logs like scrolling and swiping, which reveal exactly what users are seeing and doing (Ram et al., 2020; Reeves et al., 2021). This approach, known as Screenomics, represents a significant departure from traditional digital trace methods by offering a more accurate and comprehensive understanding of user experiences. For example, Jacobucci et al. (2024) identified digital phenotypes linked to psychiatric hospitalization for a suicidal crisis, such as spikes in substance-related words in screenshots and frequent viewing of 'murder'-themed TV shows, underscoring the value of passively colleting the content of screenshots to understand suicide risk (Jacobucci et al., 2024). Similarly, Lee et al. (2023) found that payday loan ad exposure led lower-income individuals, especially those without social safety nets, to engage with less future-oriented smartphone content, highlighting digital experiences as a key yet underexplored driver of inequality (J. Lee et al., 2023). These studies exemplify

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the value of collecting granular information about smartphone experiences, often only seconds in duration, that may be critical to understanding the interplay between digital and real-life experiences.

Despite significant interest from research communities, widespread adoption has been limited due to the lack of tools for the collection of continuous content and interaction data, because of the computational challenges to process vast collections of unstructured data generated by continuous monitoring. A handful of studies with access to skilled computer programmers and software developers have collected quality digital trace data, typically in small-scale research projects (Antal et al., 2015; Yee et al., 2023; Zingaro et al., 2024). The majority of studies, however, rely on participant data donations, which may be biased and incomplete (Ohme et al., 2024; Rodrigues et al., 2018).

Various commercial and academic offerings have sought to promote smartphone-based digital trace research (Estrin & Sim, 2010; Ferreira et al., 2015; Jardine et al., 2015; Lakshminarasimhappa, 2022; Menaspà, 2015; Onnela et al., 2021; Wang et al., 2017), as represented in **Table 1**. However, no platform to date supports both quantity-based and quality-based data collection. Many existing platforms are “closed,” and their tendency to focus collection narrowly on just a few sensor streams makes them difficult to scale and it restricts their ability to advance research. Some open-source frameworks (i.e., AWARE, Open Sensing Project, Open mHealth, KoBoToolbox) do exist, but they require substantial technical expertise and resources to customize data collection parameters (e.g., sampling interval, image quality) that align the tools with specific research objectives, making them challenging to use and replicate. These platforms also function as "closed" platforms, and only the original developers can add new features and improvements. This prevents users from expanding the capabilities of these tools to meet evolving research needs. Furthermore, there is also less transparency into the data collection and analysis processes, which is essential for ensuring scientific rigor and reproducibility. For example, researchers may not have access to the raw data or detailed documentation on how algorithms process and filter information, making it difficult to validate findings. In sum, currently available tools and frameworks for comprehensive digital trace data collection are limited in customizability, scalability, accessibility, and transparency, posing significant barriers to researchers.

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Table 1

Comparison of Digital Trace Data Collection Platforms: Key Features and Capabilities.

	Stanford Screenomics	Aware Framework	Open Sensing Project	Open mHealth	KoBoToolbox	Beiwe	Apple ResearchKit	Google Fit
Open-Source	X	X	X	X	X			
Android	X	X	X	X	X	X		X
iOS		X	X	X		X	X	X
Locations (GPS)	X	X	X	X	X	X	X	X
Accelerometer Data		X	X	X	X	X	X	
Gyroscope Data		X	X	X			X	
Activities/ Steps	X	X		X		X		X
Microphone/Audio		X	X			X	X	
Screen Activation	X	X				X		
App Usage	X	X				X		
Ambient Light		X	X	X				
Battery	X	X	X					
Power	X	X						
Network (Wi-Fi, Data Plan Connectivity)	X	X						
User-Smartphone Interactions	X							
Device Specs	X							
System Log	X							
Screenshots	X							
Customizable Features	X	X	X	X	X			
Technical Skills Required To Customize Features	Low	High	High	High	High			
Technical Skills Required To Compile the App	Low	High	High	High	High			
Self-Hosting NOT Required for Database/Server	X							
Dynamic Study Configuration	X							
Platform Expandable	X							

Note: The table excludes any platforms that collect two or fewer data types, as such platforms are less representative of comprehensive digital trace data collection tools. Technical skills “High” requires extensive software development, cloud infrastructure setup, and backend management; “Medium” requires experience configuring and integrating tools, such as basic cloud/server management and API integration; “Low” requires minimal technical skills, typically requiring the use of pre-built tools with little to no coding or backend work.

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To address these gaps, we developed an open-source smartphone-based digital trace collection platform that is easy-to-use, open-source, and expandable. The Stanford Screenomics platform consists of two native Android applications (apps) and a back-end data repository. The platform's Data Collection app is easy to deploy, offers extensive customization options enabling researchers to tailor, with minimal additional development, the types of data recorded, sampling frequency, data transfer methods, and upload cadence. The platform is specifically designed to flexibly match specific requirements of studies, and it is the only tool that allows researchers to match granular records of the actual specific screens that appear on smartphones with behaviors that precede or result from the screen experiences. Complementary to the Data Collection app, the Dashboard app supports study coordinators' real-time monitoring of participant data, identification of data collection issues, and automated reactive messaging with participants. The platform's back-end uses a scalable NoSQL database (Firebase Firestore and Google Cloud Storage) for secure, HIPAA-compliant data storage. And the platform supports the reproducibility and replicability of research studies by providing thorough documentation of data collection and processing methods,

Our goal is to support the development of versatile, user-friendly, and highly customizable digital trace collection tools, allowing for collaborative extension by the research community. In the following sections, we describe the platform's architecture, data flow, feature customization, collaborative module extension methods, and data collection and communication. We then demonstrate the utility of Stanford Screenomics for studies leveraging digital trace data with *illustrative 24-hour digital trace data* and point to the range of ways this easy-to-use open-source platform can, together with the community of developers, expand the range and reach of digital trace research. The open-source Screenomics project files, detailed component documentation, and step-by-step instructions with visual guides to support researchers use and developers extension of the platform are available here: https://github.com/iansulin/stanford_screenomics

METHODS

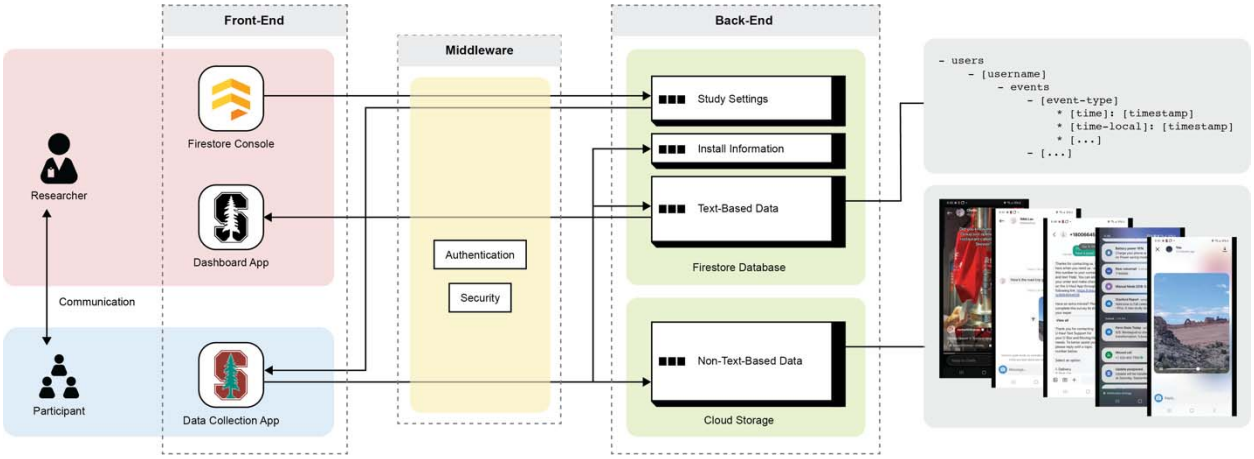
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Overall Architecture and Data Flow of the Stanford Screenomics Platform

The platform architecture consists of three main layers: front-end, middleware, and back-end. A comprehensive overview of the system's operations, platform architecture and data flow are shown in **Figure 1**. The ***front-end*** includes the Firebase console, the dashboard application, and the Screenomics data collection app. The Screenomics data collection app is an application that study participants download (e.g., from the Google Play Store or from researchers) to their phone. On launch, participants register with their study group code and ID. On successful login, the app receives the relevant study settings and begins collecting data. The data are first stored locally, and then transferred in mini-batches to ***back-end*** Firestore data bases and Cloud Storage buckets in accordance with privacy standards. Text data, like GPS coordinates, upload to Firestore databases, while non-text data, such as screenshots, upload to Google Storage folders. A ***middleware*** module handles authentication and security of communications, and transfer of data between the front end and back end. Alongside the participant-facing *data collection app* and researcher-facing *Firebase console* is a *dashboard app* that facilitates study coordinators' real-time monitoring of data collection and, if needed, communication with specific participants.

Figure 1

General platform architecture and overall data flow



Firestore Console. While the Firebase Console is not inherently designed as a front-end system, it effectively functions as one in this platform. Researchers use it to set up and launch a study by

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interacting with the [settings_profile] collection in the Firestore database. Through this console, researchers can assign each participant a study group code (e.g., intervention or control) and configure study settings for each group, such as data sampling frequency and sensor activation.

Data Collection app. The Data Collection app is designed to collect and process the different data types from smartphones. As shown in the Stanford Screenomics column in the **Table 1**, current modules facilitate collection of screenshots, app usage logs, user-smartphone interactions, location updates, physical activity data, battery status, network connectivity information, and device logs. Data collection capabilities may be easily expanded through creation of new modules to accommodate additional data types. The app runs continuously in the background, without the need for any human interaction or guidance, as participants use their smartphones normally in daily life. The app starts automatically upon the first login and remains active until logout. If the device is ever turned off completely, the app automatically resumes data collection after a device reboot. Data are collected in hidden local storage and later transferred in batches to the back end, with text data sent to Firestore and non-text data, such as screenshots, uploaded to Google Cloud Storage. The app checks connectivity based on user- or group-specific data transfer preferences set by the researchers before participant onboarding; for example, setting text data to upload over any network, while non-text data requires Wi-Fi due to size constraints.

Middleware. The middleware structure is essential for security and reliability, focusing on authentication, security measures, and monitoring capabilities. Using Firebase Authentication, the middle-ware module verifies user identities, allowing only authorized participants access to the app and safeguarding sensitive information. Firestore security rules based on user roles define specific permissions. For example, trained researchers may have full access and administrators can view data, while participants cannot access their own data. Firebase rules also enforce data validation to prevent transfer of unauthorized formats into the back-end data base. Integration with Crashlytics provides real-time error reporting and analytics, enabling the research team to monitor app performance and quickly address problems. The middleware interacts with both the front end and back end through well-defined

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APIs—specific protocols that facilitate secure communication, including RESTful endpoints for data retrieval, user authentication, and data submission. This structured middleware approach enhances data management security and efficiency to protect data while allowing researchers to maintain oversight of participants' data provision.

Back-end. The back-end of the platform uses a Firestore NoSQL database with four collections: (1) [`install`] for app installation codes, (2) [`settings-profiles`] for dynamic parameter settings, (3) [users-events] for text-based digital trace data storage, and (4) [`ticker`] for individual-level summaries of participants' recent activities (data provision). A fifth location, Google Cloud Storage, is where non-text-based data is stored in user-specific folders named by username. Both the Firestore and Google Cloud Storage folders are designed to be HIPAA-compliant.

(1) The [`install`] collection stores information about the participants who have installed the data collection app. When users (i.e., study participants) first open the data collection app, the app generates a unique install code that is stored on the local device and uploaded to the [`install`] database. These data indicate which participants have installed the app but have not completed the setup (via cross-reference with study enrollment data), and which participants have dropped out (via cross-reference with `CaptureStartupEvents` in the [`users-events`] database. Currently, these comparisons have to be done manually.

(2) The [`settings_profiles`] collection serves as a centralized hub for configuration settings tailored to various user groups, allowing researchers to dynamically assign or modify parameters throughout the study via the Firebase console. Currently, there are sixteen parameters that can be dynamically controlled to tailor the app to specific research needs, such as user profile refresh intervals and step count sampling frequencies. If a parameter like location-enabled is changed, the app will adjust GPS data collection accordingly.

(3) The [users-events] collection organizes data hierarchically under user-specific collections, accessible via unique documents named by following usernames (group code + participant ID). Each

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event log contains specific structures, such as latitude and longitude for `GPSLocationEvent` and activity types for `InteractionEvent`, along with two timestamps: standard GMT and device time.

(4) The [`ticker`] collection logs recent events for each participant, filtering [`users-events`] data to show the most recent timestamps. This log provides researchers with a quick overview of user engagement and interactions, enabling efficient monitoring of participant behavior. The ticker data are sent to the Dashboard app for real-time tracking.

(5) The Google Cloud Storage stores non-text data, namely screeenshots, in individual folders with the username. Each screenshot is saved with a file name that includes the group code, participant ID, and timestamps (e.g., `INT_101_20250122134522.jpg`). The file name is logged in the [users-events] collection under the ScreenshotEvent log whenever a screenshot is taken, allowing for easy matching later.

Dashboard Application. The purpose of the Dashboard Application is to efficiently monitor participant activity and facilitate real-time communication with participants. Upon receiving the [`ticker`] data, the Dashboard application creates priority indicators for inactive participants, flagging those who have been inactive (provided no data) for over 24 hours. This information allows researchers to monitor participants in real-time and identify individuals who may need to be contacted. The Dashboard also supports direct communication between researchers and participants via email, facilitating engagement and support throughout a study.

Setting-Up and Launching a Study

Preparing the App for Deployment. Study setup using the Stanford Screenomics Data Collection App begins with compiling the application according to specific research requirements, such as determining which data to collect through existing module selection and activation. The user-friendly compiling process, in Android Studio, allows researchers to easily configure and compile the app.

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The data collection app features a modular architecture that simplifies data collection across nine distinct modules. This modular structure allows researchers to easily add or remove data collection functions through the `ModuleController`, providing flexibility and scalability, as each module can be independently activated or deactivated based on study needs. This aspect of architecture allows the app to be personalized for any given study. In practice, researchers download the open-source project files of the app and open them in Android Studio, which is available for free. Within Android Studio, the Module Controller can be located in the left-side interface list view, and it serves as the central activation/deactivation interface, listing all available data collection modules (currently nine) with Boolean values: `true` (activated) or `false` (deactivated). Before compiling the app, researchers can set the Boolean values according to their specific study requirements for data collection. The activation or deactivation of a module does not impact the overall performance of the app, as each module operates independently. Some features, like step count and GPS data collection, can be dynamically turned on or off throughout the study, allowing a single app version to accommodate changes in data collection. However, once a module is deactivated, it cannot be reactivated later, thereby requiring separate app compilations for each study group.

Additionally, to prevent device storage overload, the app automatically restricts screenshot capture when the user device's available storage falls below 50 MB. This architecture ensures that researchers can efficiently customize the app for their studies without extensive technical expertise and participants can simultaneously use their smartphone as normal while providing rich multimodal data.

In addition to activating modules, essential configuration steps—such as setting up an app password and defining a consent form—can be easily modified within two dedicated configuration files, eliminating the need to scroll through code to find placeholder text. The consent form serves as a prominent disclosure, required by Google's User Data Policy for Android apps that collect personal and sensitive information (https://developers.google.com/terms/api-services-user-data-policy). The Google policy mandates that developers clearly inform users about data collection practices and obtain their informed consent. It is important to note that Google's consent form must be added to, and may not

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replace, Institutional Review Board (IRB) consent forms. Therefore, two consent forms are generally required: one for Google policy compliance and one for ethical research approval through an IRB.

Researchers must also configure Firestore, Google Cloud Storage, and Crashlytics by registering the app in a new Firestore project. When they do this, a JSON file is generated automatically, which should then be placed in the main app and the database manager modules of the Screenomics app using Android Studio. This drag-and-drop action automatically sets up Firestore, Google Cloud Storage, and Crashlytics. Finally, researchers need to ensure that Crashlytics is enabled in the Firebase for their new project, and failing to do so would prevent the app from capturing and reporting crashes or errors, making it difficult to maintain reliability and improve user experience. Optionally, researchers can also configure Firestore rules for data security.

Once all configurations are finalized, compiling the app is straightforward. Researchers select "`Build`" from the menu in Android Studio, then choose "`Build Bundle(s)/APK(s)`" and "`Build APK(s)`," after which a notification will confirm that the APK (Android Package Kit) file has been generated as a ready-to-use installation package for Android devices. To distribute the APK to participants, researchers can share it via email, cloud storage links, or secure file-sharing methods. Participants can then install the app by downloading the APK file onto their Android devices, opening the APK file and following the on-screen instructions. Thorough testing should confirm that the app meets the study's specifications, ensuring participants have access to the latest features and updates.

Dynamic Controller Parameter Setup. Prior to onboarding participants, researchers can customize the data collection app's features to align with specific study requirements, including adjustments to sampling intervals and data transfer network preferences. The app periodically retrieves the latest parameter values at intervals specified in the settings profiles (through a dynamic parameter called '`settings-refresh-interval`'), allowing researchers to update data collection methods as needed, without needing to recompile the app or contact participants to makes changes. This dynamic control allows researchers to balance the frequency of updates with considerations for device battery life, storage, privacy, and study needs. Currently, sixteen features can be dynamically controlled to tailor the

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app to specific research needs. There are no fixed default parameter values, as these can vary widely depending on the number of activated modules. For example, a 5-second sampling interval for GPS coordinates may not impact performance if only the location module is active. However, if combined with a screenshot module set to capture every 5 seconds, this frequency could strain system performance or rapidly drain the battery. The `settings` section in our GitHub documentation provides recommended minimum parameter values (highest resolution) for a case where all nine modules are activated.

When the data collection app is configured with the `google-services.json` file, the app automatically creates four collections in the Firestore console: [`install`], [`settings-profiles`], [`users`], and [`ticker`]. To set up dynamic controller parameters, researchers must first create a new document named "`_default_`" under the [`settings-profiles`] collection. In this document, researchers must add all parameters from the full list of available parameters for the app version and set default values for each parameter according to the study needs. The data collection app imports these default values during a participant's first login. If all parameters are not specified in the "`_default_`" document, the app will lack reference values, potentially hindering its ability to collect data effectively and impacting overall study outcomes. Therefore, it is crucial to finalize these settings before onboarding participants.

Researchers can create as many additional profiles as needed for different study groups by adding group codes, similar to how the default profile is set up. For example, if participants have varying data transfer preferences, two profiles can be created with the group codes [`WIFI`] for those who prefer transferring data over Wi-Fi only and [`DATA`] for those willing to use their mobile data plan. These group profiles do not need to include all parameters from the list; only those that are relevant need to be specified. Researchers can configure data transfer settings differently for each group while keeping other study parameters consistent. This allows for tailored data collection strategies based on the specific requirements of each group. The group codes are later assigned to participants who will use them along with other information provided by researchers to register in the app during onboarding. If a participant

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registers in the app with a group code that does not match any created profiles, they will inherit the default setting parameter values specified in the "`_default_`" document.

Participant Onboarding. To initiate a study with the Stanford Screenomics Data Collection App, researchers must first establish participant groups, such as intervention and control groups. Each participant requires a unique group code (e.g., "`WIFI`" for the over Wi-Fi only group and "`DATA`" for the unrestricted data group), an individual ID number (e.g., `101`, `102`), an email address, and a password for registration and login. The password should be configured during the app's setup before compilation. While researchers provide the group codes, individual ID numbers, and password, participants must also supply their own active email addresses during onboarding. The email is required for Firebase authentication, restricted database access, and researcher-participant communication via the Dashboard app. However, email addresses are stored only within the Firestore authentication system and are not linked to study data, and they are not visible within the app, database, or storage. All collected data are associated with a unique username, composed of a group code and individual ID numbers, ensuring that study data remains non-identifiable through email.

Upon first login, participants will see a one-time pop-up prompting them to review and sign the Google permissions consent forms. If they agree, they will then be asked to grant necessary permissions for the app to function effectively, such as access to precise location data and media projection features, depending on the modules activated during app compilation. Once these permissions are granted, data collection begins passively in the background, ensuring an unobtrusive experience. Screen recording is continuous unless participants log out of the application or choose to pause screen recording. The app's main interface will display a single button for participants to pause or resume screen recording at any time, allowing them to manage storage, battery, and privacy concerns. To ensure continuous data collection, the app sends reminder notifications if a participant pauses the screenshot collection: one message after 30 minutes, and then at 7 AM and 7 PM for the next two days, totaling five notifications. If participants do not agree to the consent or fail to provide all required permissions, the app will not advance to data collection. Consent and permission requests will not reappear on subsequent logins unless

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permissions have been revoked. If participants revoke any permissions during data collection, the app will pause that specific data collection. Upon their next app launch – whether by actively opening the app, rebooting the device, or tapping a notification sent after 30 minutes of pausing – they will be prompted to re-grant the revoked permissions, ensuring the study remains compliant with ethical standards.

Monitoring of Data Flow. Effective monitoring of data flow is essential for maintaining the integrity and reliability of research outcomes. By continuously tracking participant engagement and data collection processes, researchers can make informed adjustments, address potential issues in real time, and enhance data quality. In Stanford Screenomics, two primary methods are employed for monitoring data flow: the [`users-events`] collection and the [`ticker`] collection in Firestore. The [`users-events`] collection provides detailed insights into individual participant actions, while the [ticker] collection offers a streamlined overview of user engagement.

The [`users-events`] collection captures a range of text-based event data. An event denotes a specific action that occurs at a particular moment, encompassing various user activities such as app logins and logouts, pausing or resuming screenshot functions, and interactions with notifications (e.g., read or ignored). It also includes all text-based event data captured by activated modules, as well as device system and app lifecycle events, such as device reboots and automatic app launches. Events are organized by type and timestamps, often accompanied by additional metadata specific to each event. For non-text-based events, a dual approach is employed: when an event occurs, the actual data—such as screenshots—is sent to Cloud Storage, while simultaneously, the [`users-events`] collection logs that the event has taken place, including corresponding timestamps and metadata such as the file location URL in Cloud Storage. This approach allows researchers to track both non-text-based and text-based data within the same structure and in one location. Consequently, this alignment facilitates not only the quick identification of trends but also enables comprehensive in-depth analysis later.

The [`ticker`] collection filters the [`users-events`] collection data to create individual user documents, which list each event along with the most recent timestamp. This collection is particularly

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beneficial as the number of app users increases, as manually checking each participant's events for recent activity can become labor-intensive. When a participant's app syncs their events to the [`users-events`] collection, the corresponding fields in the [ticker] collection are updated to reflect recent activity across different event types. This [`ticker`] data is organized and displayed in the Dashboard app, allowing researchers to easily view all study participants' usernames ranked by the length of inactivity on the main interface of the app. Users who have been inactive across all events for more than 24 hours are highlighted in red. Each username is expandable on tap, revealing a detailed view of all events and the most recent activity timestamps. Researchers can also initiate email communication with participants directly from this view if needed.

Platform Extension

The Stanford Screenomics Data Collection App is designed with a modular architecture that facilitates platform extension through easy plug-in integration of new functions, while allowing developers to activate or deactivate existing modules. Currently, the app includes two core base modules—`ModuleManager` and `DatabaseManager`—and nine distinct data collection modules: screenshots, app usage logs, user-smartphone interactions, location updates, physical activity, battery status, system power, network connectivity information, and device specs logs. The core base modules provide essential functionalities that form a robust foundation for each data collection module's operations. This architecture simplifies the integration of new modules by enabling them to easily adopt the tools and frameworks from the base modules, allowing developers to ensure their custom data collection modules align seamlessly with the overall app requirements regarding data structure, storage setup, network preferences, and data transfer methods.

Base Module 1: Module Manager. The Module Manager serves as the central control system, overseeing the operational status of various data collection modules. Key functionalities include centralized event record management and timestamp definition, which together create a cohesive

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environment that enhances consistency in logging and data management. All modules in the Stanford Screenomics Data Collection App follow a uniform data structure within Firestore, storing data under a user's collection as a list of event documents. Each event in this list is organized by event type and includes two timestamps—one for standard time zone and one for the user device's system time (usually in the user's local time zone)—along with a unique ID and additional event-specific metadata. The event record management and timestamp definition functionalities facilitate this organization. Additionally, the `ModuleManager` provides a collection of reusable components (e.g., classes, methods) for various features. For example, a method for reading battery state changes can be employed in the location module to pause data collection when the battery level drops below a critical threshold, conserving energy. In the battery status module, the same method can log battery status at predefined intervals. This capability to share reusable components across modules streamlines development, promotes efficiency, and provides insights without redundant code, enabling new data collection modules to quickly adopt and integrate these functionalities. Lastly, the module controller within the `ModuleManager` allows developers to turn on or off existing modules without impacting overall app functionalities.

Base Module 2: Database Manager. The `DatabaseManager` is essential for data storage and retrieval, serving as the primary repository for data transfer preferences. It includes comprehensive functionalities for local and external storage setup, network configuration, data syncing, and security, all defined as reusable components. The app stores data collected from each module locally on the device until an internet connection is available. Once online, text-based data is transferred to Firestore and non-text-based data to Cloud Storage in batches, with transferred data automatically deleted from local storage to free up space for ongoing data collection. The local and external storage setup functionality manages this process seamlessly when used in a module. Regarding data transfer, each module allows researchers to set preferences for restricting transfers to Wi-Fi only or allowing any internet connection, using dynamic parameters. The network configuration functionality retrieves these parameters from the Firebase console to make data transfer decisions based on network preferences. To ensure data in Firestore and Cloud Storage remains current, a regular data syncing process periodically checks local

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storage. Additionally, the security functionality oversees storage solutions for sensitive information, such as authentication details, throughout each process.

Module Dependencies. To support the platform's extension through the addition of new modules, it is essential to understand its dependencies which can be categorized into three types: modular, internal, and external. Modular dependencies consist of distinct functionalities imported from base modules, organized into separate data collection modules. For example, text-based data collection modules utilize the `TextBasedEventData` class from the `ModuleManager` base module, while non-text-based modules depend on `NonTextBasedEventData` class, both requiring `EventTimestamp` for consistent timestamp formats. Internal dependencies include classes and libraries from the Android framework and Java standard libraries, essential for basic app functionality such as component management and communication operations. External dependencies, often optional, include third-party libraries that enhance capabilities beyond the Android SDK, such as advanced UI components or improved networking features.

The development process for specific modules illustrates these dependency types in action defining its purpose and establishing a clear structure. For instance, when developing a “Location Data Collection” module that periodically collects GPS coordinates, internal dependencies such as `android.Manifest` for location access permissions, `android.os` for system interactions, and `java.util` for data structures are crucial for foundational functionality. The module also relies on the Google Play Services location API as an external dependency for accurate GPS tracking, enabling the collection of real-time longitude and latitude data. Lastly, modular dependencies like `ModuleController` class from `ModuleManager` base module enable the activation or deactivation of individual data collection modules, while `EventTimestamp` class ensures consistent timestamping of each GPS coordinate log. The `ModuleCharacteristics` class standardizes the structure of location event data, capturing key details like class name and event type. The `EventOperationManager` class from `DatabaseManager` base module processes this

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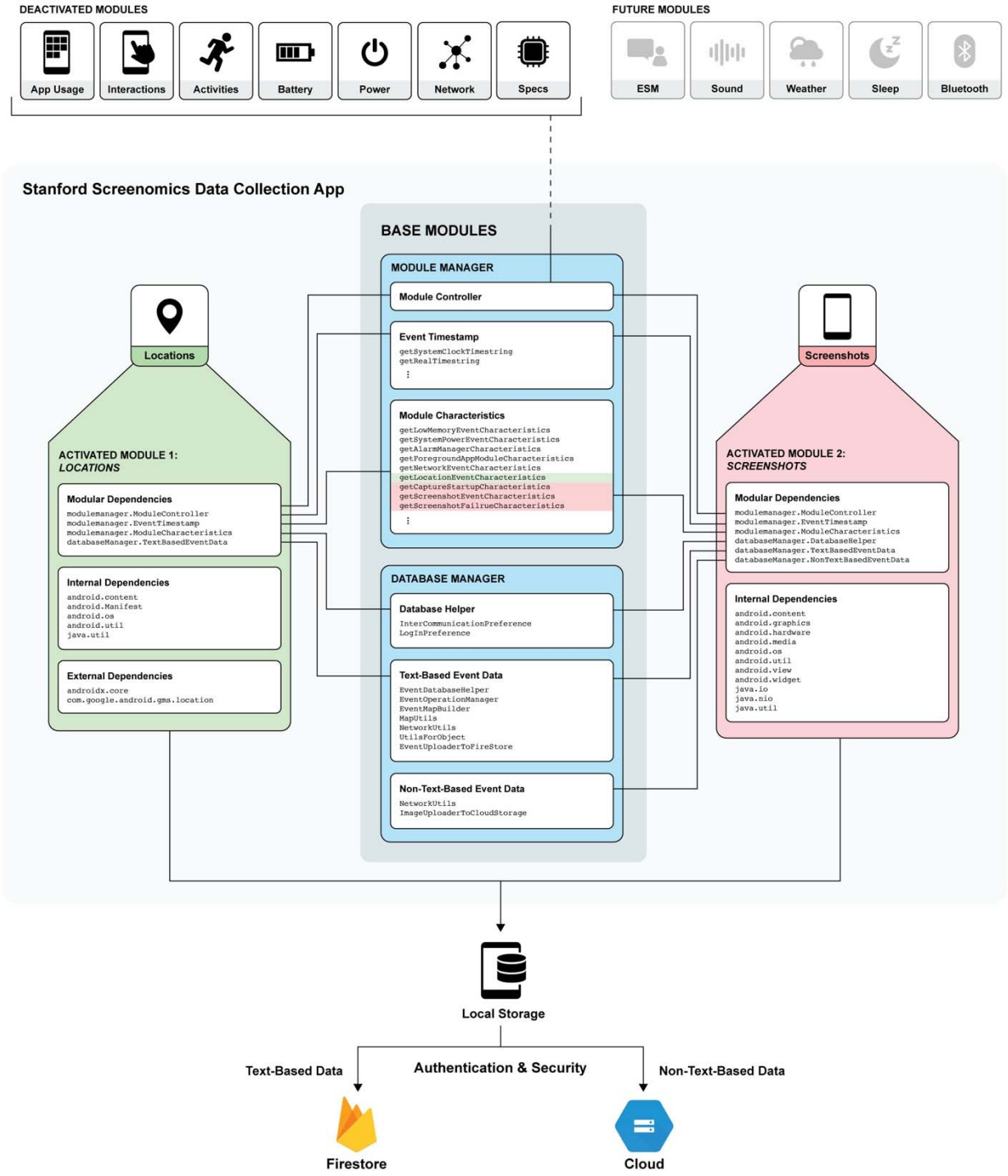
standardized data. It formats the data, buffers it in memory, stores in local storage, and performs batch uploads to Firestore using `EventData.Builder`. Additionally, `DatabaseManager` base module provides space researchers to add dynamically parameters through `SettingsManager` class.

In contrast, when developing a Screenshot collection module, the process shares similarities but includes unique requirements. This module would integrate additional internal dependencies such as `android.graphics` for bitmap manipulation and `android.media` for screen capture through the `MediaProjection` API. While this module does not require external dependencies, it needs additional modular dependencies like `NonTextBasedEventData` class from the `DatabaseManager` base module to manage and transfer of screenshot images to Google Cloud Storage. **Figure 2** illustrates module dependencies of the Screenomics Data Collection App platform.

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Figure 2

Illustrative Diagram of Stanford Screenomics Data Collection Module Dependencies



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RESULTS

Illustrative Data

We demonstrate the utility of Stanford Screenomics platform for digital trace research with *illustrative 24-hour digital trace data* collected by the developer (IK) using a Samsung Galaxy S21 smartphone. These data were only collected for demonstration of the platform and app functionalities. The data are not meant to provide generalizations about human behavior and thus do not constitute human subjects research.

Activated modules and parameters. The Data Collection App was compiled with all nine currently available collection modules: (1) the *Screenshots* module captures screenshots at defined intervals, saves the screenshot images, and logs information about the screenshot taken (e.g., image file name and screenshot timestamp), (2) the *Apps* module logs the currently active application by checking the foreground app periodically and recording changes with timestamps, (3) the *Interactions* module tracks user events such as scrolls, clicks, and gestures through accessibility services, (4) the *Locations* module logs latitude and longitude from device's GPS sensor at set intervals, pausing when no updates are available, (5) the *Activities* module tracks user step counts at fixed intervals, (6) the *Battery* module monitors battery levels (low below 15%, okay above 20%) and charging events, (7) the *Power* module logs changes in screen state, noting whether activation is due to user interaction, (8) the *Network* module tracks connectivity changes (Wi-Fi and cellular), and (9) the *Specs* module collects basic device specifications upon account creation. The Screenshots, Locations, and Activities modules log data at researcher-defined intervals, while the other modules record data based on specific events. Data collection interval parameters were set to 5 seconds for screenshots, 1 minute for locations, and 5 minutes for aggregated step counts.

Technical performance of platform. Generally, developers try to keep the size of complex app APKs under 50 MB. Here, the compiled app's APK size of 10.56 MB is well within acceptable limits given that this is a modular app with a total of 11 different modules. Cache size of 67 KB is excellent and indicated efficient storage management. Even with continuous data logging, the app's impact on device

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performance was negligible. Generally, keeping RAM usage under 200 MB during active use is essential for smooth performance. During the 24-hour data collection period, the Screenomics app's RAM usage peaked at 105 MB (approximately 1.28% of the total available RAM). Generally, CPU usage should remain below 15% to ensure responsiveness. Here, CPU usage averaged 2.1% during active sessions. Typically, less than 5% battery drain per hour is considered optimal, allowing for a target screen on time of at least 6-8 hours. The Screenomics app drained approximately 1% per hour during active use, indicating minimal power consumption. It is unlikely to significantly impact battery life or be noticeable to users during regular smartphone use. Overall, our testing results indicated that even when collecting high-density data (e.g., location interval of 1 minute) the app performed well, storage management was efficient, and the app's consumption of resources remained within reasonable limits.

Although researchers do not have direct access to these metrics, there are several ways to check for potential issues, in addition to the Crashlytics and Dashboard activities mentioned previously. Researchers can refer to the `ScreenshotUploadEvents` document in the user-events collection of the Firestore database. First, the remaining-bytes field indicates the available storage space on the user's device, measured in bytes. While not directly related to uploading, this information helps monitor whether users are running out of space. Second, the error field provides a `yes`/`no` value indicating whether the specific upload event encountered an error. Any `ScreenshotUploadEvent` suggesting an upload did not complete will show "`yes`" as the error value.

User experience. Across the 24-hour period, there were no noticeable impacts on device use. As intended, the app operated unobtrusively in the background, and did not interfere with the user's daily activities. There was no noticeable difference in battery drain, no storage issues, and no app performance problems. The Android system performance remained consistent, with no delays, lag, or interruptions. In line with the intended design, the user was fully informed about what data were being collected, at the start of data collection, and that they had the ability to stop and start the collection at any time via an informed consent process that users engage when they first open the app and register with their

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researcher-assigned study group credentials and ID code. Along with the IRB-protocols we have used in all Screenomics studies, Google's clear and transparent consent procedures educate users about the data collection procedures and empower them to make informed decisions about their participation on an ongoing basis. We generally find that users are fully aware of the data collection and that, unlike many other apps, this app allows users to retain control of data collection and data. Users have the ability to pause/resume screenshot captures at any time with a few clicks, to choose precise or approximate (1-2 mile boundary) location, and to temporarily halt all data collection when they log out of the app.

Table 2

Summary of Digital Traces Collected during 24-hour Study Period.

Module	**Data Collected**	**Quantity**	**Interval/Frequency**
Screenshots	Screenshots captured	1,729	Every 5 seconds
	Screenshot data collection paused	0	Upon user-initiation
	Screenshot data collection resumed	2	Upon user-initiation or after reboot
App Usage	Foreground app changes	45	As app transitions occur
Interactions	Scroll-up	785	As interactions occur
	Scroll-down	162	As interactions occur
	Scroll-left	69	As interactions occur
	Scroll-right	64	As interactions occur
	Clicked	1,363	As interactions occur
	Long-clicked	12	As interactions occur
Locations	GPS coordinates (latitude/longitude)	810	Every 1 minute
Activities	Step counts	193	Every 5 minutes
Battery	Battery state: low (<15%)	1	System alert
	Battery state: okay (>20%)	1	System alert
	Device connected to a charger	1	As charging status changes
	Device disconnected from a charger	1	As charging status changes
Power	Off	1	As system state changes
Network	Connected to Wi-Fi	24	As connectivity changes
	Disconnected from Wi-Fi	3	As connectivity changes
	Connected to data plan	20	As connectivity changes
	Disconnected from data plan	1	As connectivity changes
Specs	Device specifications	1	Upon account creation

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Data Summary. A summary of the types and quantity of data obtained through each of the nine modules during the 24-hour observation period are shown in **Table 2**. The total size of the text-based data was 6.08 MB. The total size of the non-text-based data (i.e., screenshots) was 604.15 MB. The Screenshots module collected 1,729 screenshots that chronicled (at 5 second intervals) visual content that appeared on the smartphone throughout the day during approximately 144.5 minutes (~ 2.5 hours) of screen time. Simultaneously, the Location module logged 1,440 GPS coordinates and the Activities module recorded a total of 1,626 step counts (in 193 5-minute intervals). The Apps module captured 62 changes among 25 unique foreground applications (counted based on unique app package names logged as metadata for each event). The Interactions module logged a total of 2,455 user-device interactions, the majority of which were "`clicks`" (1,363 simple taps on the screen) that indicate button presses or typing on a keyboard (e.g., when texting or emailing). The Battery module recorded one low battery alert at 10% and one charging event, while the Network module documented a total of 48 changes in internet connectivity. During the 24-hour period, the data were periodically transferred in small batches from local storage to Firestore and Cloud Storage when the device was connected to Wi-Fi (60 successful upload events in total recorded by the app package itself, not through a specific module). Overall, the smooth, unobtrusive, and uninterrupted data collection produced a rich multimodal data that is then easily processed and examined.

DISCUSSION

Digital trace data collection platforms offer a possibility to further develop and expand the range of insights obtained from diverse research projects across multiple disciplines. A growing body of evidence highlights the value of digital trace data in monitoring and detecting various social, behavioral, cognitive, affective, physiological, and environmental changes, providing deeper insights into social ecology and ultimately improving the management of various associated health conditions (Freelon, 2014; Huckvale et al., 2019; Insel, 2017; Jungherr et al., 2017; Liang et al., 2019; Ohme et al., 2024; Thylstrup, 2019). The proliferation of personal smartphone devices, coupled with advancements in

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technology, has enabled unprecedented fine-grained and objective data collection (Cheng et al., 2017). However, as shown in **Table 1**, very few of the currently available data collection tools allow researchers to curate their studies effectively due to challenges including restricted scalability, limited customizability, lack of transparency, and the substantial technical expertise required to tailor the tool to the specific requirements of a study, such as software development, data engineering, and knowledge of cloud infrastructure—that are rarely possessed by many behavioral, social, and medical researchers.

Screenomics platform. To address these gaps, we developed and introduce here an easy-to-use open-source platform that enables in-situ, real-time capture of multimodal digital traces from users' smartphones as they go about their everyday lives. Building on the initial Screenomics app introduced in 2019 (Reeves et al., 2021), the new Stanford Screenomics platform provides a robust framework that allows researchers to capture and analyze the full array of digital life experiences that flow across and through individuals' smartphones. Extending and integrating existing solutions into larger-scale clinical or research systems usually requires extensive modifications to the underlying architecture of data collection tools, which can hinder research adaptability and responsiveness to evolving study needs. Earlier research has indicated the importance of a flexible framework that accommodates diverse research methodologies and data collection strategies. This expanded framework enables researchers to explore user behaviors across multiple time scales, investigating how moment-to-moment exposure to digital content influences long-term patterns such as content-switching behaviors, technology addiction, physical activity, emotional well-being, and how personal characteristics shape digital engagement, thereby greatly enriching our understanding of the interplay between technology and human behavior and health. The platform has now evolved into a comprehensive digital trace data collection tool by integrating a broader array of data types beyond just screenshots and app usage, offering several significant advantages.

Technical Advantages. The modular architecture design used in the new Stanford Screenomics platform allows researchers to tailor their data collection processes without being constrained by rigid application structure. The modular approach not only enhances the system's extensibility but also enables anyone to use partial functionality required for their specific use case. The Stanford Screenomics platform

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further applies this modularization to encourage community contributions by providing reusable solutions that enable developers to create new modules and expand the platform's capabilities through well-defined extension points, and allowing for free sharing of select functionalities. This approach also facilitates co-maintenance of transparent high security and privacy standards. Our goal is to create a robust ecosystem where researchers can efficiently customize their tools for specific studies while ensuring compliance with established data collection and privacy standards. We plan to introduce more data collection modules over time to enable the collection of different digital trace data sources, including Bluetooth connections and audio samples. We also hope to have an iOS version of our platform alongside the Android version, although iOS currently restricts some features, such as screenshot data collection, making them impossible to implement.

Technical Challenges and Open-Source Extension. While the modular approach provides flexibility in feature customization and an easy solution for utilizing selected functionalities in the Screenomics platform, it also presents several challenges related to device dependency. The app's performance is significantly influenced by the specific capabilities of the devices on which it operates. Frequent updates to the Android operating system can lead to changes that impact app performance, such as new permissions or modifications in how features are utilized, potentially disrupting data collection processes. Additionally, despite extensive testing, performance can vary greatly due to individual device specifications, such as processor speed and sensor accuracy, with older devices often struggling to manage simultaneous data collection from multiple modules. This variability may result in inconsistent user experiences and affect user engagement. Furthermore, multi-module apps tend to be more resource-heavy than single-module apps, potentially leading to increased battery consumption and reduced performance. As new devices are released, compatibility issues may also arise, necessitating ongoing updates to maintain functionality across a diverse range of devices. Our hope is, by releasing the platform as open-source, we can enhance our ongoing efforts in maintenance and development, allowing the broader research community to contribute as well, thereby enabling timely updates and continuous improvements. Much like WordPress (www.WordPress.com), which evolved from a simple blogging tool

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into the leading open-source content management system—now powering over 40% of all websites on the internet through extensive independent developer contributions—Stanford Screenomics holds the potential to thrive through shared endeavors.

Research advantages. The new Stanford Screenomics platform expands a variety of research possibilities. First, by combining multimodal data sources, researchers can cross-validate findings, improving the reliability and robustness of conclusions compared to relying on a single data type. For example, in a study exploring the relationship between social media content consumption and mental well-being, incorporating app usage data and GPS location data alongside screenshots (which capture content displayed) would enable researchers to assess whether changes in mental health correlate with specific locations, certain app functions and/or particular content. This cross-validation would not only enhance the reliability of conclusions but also would help rule out confounding variables, ensuring that observed effects on the outcome of interest are genuine.

Second, the integration of multiple data sources would allow for the application of advanced analytics—such as machine learning or predictive dynamic modeling—which could uncover complex interactions between often intertwined domains across multiple time scales and contexts. These advanced techniques offer more nuanced interpretations of how contextual and environmental factors influence both momentary and long-term behavioral and health outcomes. Such analyses would be impossible to apply with only one or two data sources; the richness of multimodal data opens new opportunities for more comprehensive insights.

Third, with access to screenshots and user-smartphone interaction data adding to other smartphone use and behavioral metrics, researchers can now identify complex multidimensional, digital phenotypes that offer deeper insights into individual's life stages and transitions–from second-by-second changes in screen experiences to characterizations of screen experiences over days, weeks, and even years. For instance, while screenshots may reveal that a person has shared on social media their goal of achieving 10,000 steps daily as part of a fitness regimen and subscribes fitness models' feed, step count data can confirm whether they are meeting that goal, and GPS data can indicate whether they are

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engaging in indoor or outdoor activities. This multi-dimensional approach provides a clearer picture of the person's motivation and behavior, creating a richer, more comprehensive individual profile. Finally, the granular real-time digital trace data combined with advanced analytics, enables the design and delivery of personalized, adaptive interventions. For example, if a person's social media posts suggest an interest in achieving daily step goals but their step count data repeatedly shows low engagement on Mondays while playing games, targeted content—such as motivational messages or goal reminders—can be delivered to encourage action every Monday when starting game play. These insights allow dynamic adjustments to intervention strategies based on changing patterns or participant feedback, ultimately improving behavioral and health outcomes. This is particularly valuable in longitudinal intervention studies, where researchers can adapt interventions to optimize impact and sustain positive behavior change.

Ethics. While the platform offers valuable insights for advancing research and improving health outcomes, its ability to capture highly detailed personal information and digital trace data creates a risk of misuse by bad actors. The data collected through the Screenomics platform could be exploited for purposes such as surveillance, targeted manipulation, or unauthorized commercial use, potentially leading to violations of privacy, coercive cognitive or behavioral modifications, or even social control. To mitigate these risks, the research community must take proactive measures to ensure ethical use. This includes implanting robust data privacy protections, obtaining informed consent, and establishing clear boundaries around data sharing (Maeckelberghe et al., 2023; Nebeker et al., 2020, 2021). Researchers should adopt the principle of data minimization—collecting only the data that is strictly necessary for the research (Dunseath et al., 2018; Maeckelberghe et al., 2023; Nebeker et al., 2019, 2021). This principle should also extend to limiting data retention times and ensuring that data is only stored as long as required for legitimate research purposes, thus preventing the accumulation of unnecessary data that could later be misused (Nebeker et al., 2021). For the purpose of data sharing and management, summaries of key data features could be extracted and archived in place of raw data to support open science and reproducibility. Additionally, researchers should prioritize transparency with participants and consider conducting regular

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audits to ensure data are being used responsibly (Filkins et al., 2016; Nebeker et al., 2020). This includes being transparent about how data are analyzed within analytical algorithms to inform decisions. Algorithmic transparency helps mitigate concerns about opaque or biased decision-making processes and provides users with a clearer understanding of how their data are being used for research (Watson & Nations, 2019; Wrzus & Schoedel, 2023). By adhering to such rigorous ethical standards and maintaining oversight, the research community can help prevent harmful exploitation and ensure that the insights gained from the platform are used responsibly and for the public good.

CONCLUSION

Using smartphone-based digital trace data offers a promising path toward providing more detailed insights into human behavior and well-being, reducing costs, understanding how smartphones are important in a broad spectrum of life, advancing personalized healthcare, and creating new theories of human behavior that require granular visibility into the details of moment-by-moment interactions. The Stanford Screenomics platform represents a significant step forward by offering an open-source, customizable framework for unobtrusive, multimodal data collection, including screenshots. By addressing limitations in scalability, customizability, and transparency found in existing tools—and by simultaneously capturing quantity-based and content-based data—it empowers researchers to conduct large-scale, flexible, cost-effective, and content-aware studies, yielding unprecedented insights into human behavior and health. With features like easy deployment, real-time monitoring, and adaptability to various research needs, the platform is poised for broad application across diverse research areas. As digital trace research continues to grow, we are committed to expanding the platform's capabilities along with an open source community, supporting collaboration, and ensuring reproducibility, ultimately enabling more comprehensive studies and facilitating the development of personalized interventions that improve health outcomes for individuals and populations.

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OPEN PRACTICES

Availability of data and materials: The text-based, illustrative 24-hour digital trace data collected using the Stanford Screenomics platform is available from the corresponding author upon request. The original screenshot are not available, as they have not been processed to protect the privacy of individuals whose information was captured.

Code availability: The source code for the Stanford Screenomics platform developed by I.K. and J.B. is available for public access at: https://github.com/iansulin/stanford_screenomics

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