Supporting Self-Awareness of Smartphone Use with Passive Sensing and LLM-Driven Feedback

Nigel Sjölin Grech*
nsjgr@dtu.dk
Technical University of Denmark
Kgs Lyngby, Denmark

Gabriella Trasciatti*
trasciatti@di.uniroma1.it
Sapienza University of Rome
Rome, Italy

ABSTRACT

Smartphones provide considerable benefits in every day life, but can negatively impact users' mental well-being when used excessively. While individuals can proactively manage their smartphone usage, accurately estimating usage time remains challenging. Recent advancements in Large Language Models (LLMs) offer significant potential to increase users' awareness of their smartphone usage habits through more natural conversational interactions. Current approaches employing LLMs for smartphone usage regulation primarily focus on directly restricting usage or providing conversational coaching and persuasive interactions. However, there is limited research on methods designed specifically to enhance users' awareness of their habits and support sustained self-regulation. This paper presents a prototype system designed to promote self-awareness and support behaviour alignment around smartphone use. The system integrates passive monitoring of smartphone activity and physical movement with structured daily self-reflection, goal setting, and LLM-generated feedback. Users receive personalised, reflective summaries informed by both sensor data and self-reported evaluations, with feedback tailored based on the alignment between observed and intended actions. The system was developed as a rapid prototype during a summer school workshop, and its feasibility was demonstrated through a series of simulated usage scenarios.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile devices**; **Personal digital assistants**.

KEYWORDS

Large Language Models; Mental Wellbeing; Ubiquitous Computing; Mobile Sensing

ACM Reference Format:
Nigel Sjölin Grech and Gabriella Trasciatti. 2025. Supporting Self-Awareness of Smartphone Use with Passive Sensing and LLM-Driven Feedback. In *Companion of the the 2025 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp Companion '25), October 12–16, 2025, Espoo, Finland*. ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3714394.3756242

*Both authors contributed equally to this research.

UbiComp Companion '25, October 12–16, 2025, Espoo, Finland

ACM ISBN 979-8-4007-1477-1/2025/10
https://doi.org/10.1145/3714394.3756242

1 INTRODUCTION

Smartphones offer a wide range of services, making them ubiquitous in everyday life. While this accessibility brings many benefits, excessive screen time has become a growing concern. Prolonged use of smartphones can negatively impact users' well-being, provoking higher values of stress, depression, anxiety, and sleep disturbances[4, 18]. To address issues associated with excessive smartphone use, individuals can adopt *self-care* practices. Self-care involves proactively managing one's mental health and overall wellness, either independently through available resources or with guidance from professionals[11, 15]. With recent advancements in artificial intelligence and conversational agents, numerous emerging studies have started exploring their integration into self-care applications, including chatbot coaches[3, 9, 11], journaling assistants[13], and intelligent smartphone usage limiters[14, 19]. These systems can be especially effective when they incorporate data collected directly from users' smartphones, as this enriches the agent's context and enables more relevant feedback. Rather than presenting raw usage statistics, such data can be processed and conveyed in more meaningful and personalized ways. This is especially important, as there is often a discrepancy between actual smartphone usage and users' perception of it[5, 10]. In this work, we present a prototype system designed to promote self-awareness and behaviour alignment through a combination of passive smartphone sensing, structured goal setting, and LLM-generated reflective feedback. Users begin each day by setting a personal goal, such as reducing phone use or increasing physical activity. The latter may serve as a healthy alternative that shifts attention away from screen time, helping individuals move their behaviour in a more positive direction. Throughout the day, the system collects objective data including app usage and mobility patterns via AWARE-Light. Users also complete brief self-reports assessing their progress. At the end of the day, all collected information is aggregated and transformed into a textual summary that is provided to a Large Language Model (LLM) agent. The agent then uses this context to offer personalized feedback and guidance to help the user move toward their goal. At the same time, detailed smartphone usage data and physical activity are presented to the user, offering a transparent overview of their behaviour. We identify four key user scenarios: (1) the user is on track and aware of their smartphone use and physical activity; (2) the user is off track but still aware; (3) the user is off track and unaware; and (4) the user is aware but not aligned with their goal. The agent identifies which of these scenarios best fits the user's situation and responds accordingly—either by encouraging the user to stay on track or by gently prompting them to reflect, adjust their expectations, or re-engage with their goal. To the best of our knowledge, this work is among the first to rapidly prototype an integrated system combining passive smartphone sensing, goal setting, self-reflection, and LLM-assisted feedback for promoting digital well-being. This work demonstrates the feasibility of integrating self-reporting, smartphone sensing, and LLM-generated feedback within a lightweight prototype to support self-awareness and goal alignment around smartphone use.

2 RELATED WORKS

2.1 Smartphone Sensing and Mental Well-being

Smartphones have become research tools for behaviour and mental health sensing, enabling the the use of digital phenotyping in analysis and assessment of health data [2]. Early works like StudentLife demonstrated that phone data (such as location, activity, call logs) can be used to estimate stress and well-being in college students [17]. However, developing smartphone sensing applications remains a challenge due to the diverse skill sets required and significant device and platform heterogeneity . This often leads researchers to build standalone apps for individual studies, limiting reproducibility. Modern cross-platform frameworks, such as AWARE [16] and CARP [1], address these issues by providing reusable, multi-device abstractions that simplify data collection.

Frameworks like AWARE-Light have been widely adopted in mental health studies for unobtrusive and scalable sensing [16]. For instance, Moshe et al. conducted a 60-person study integrating smartphone usage, GPS data, and wearable sleep and Heart rate variability (HRV) measurements, which demonstrated correlations between reduced mobility and higher depression scores, and between poor sleep quality and anxiety symptoms [12]. Another study leveraging AWARE mobile sensing framework was conducted on 41 adolescents diagnosed with depression. This work indicated that decreased mobility and increased screen time were good predictors of nomophobia and depression [21].

Effective mental health interventions require self-awareness and mindful behaviour change. A recent systematic review by Zhu et al. identified self-monitoring, goal-setting, and prompts/cues as the most effective techniques for digital habit interventions [23].The "Not Less, But Better" app demonstrated this by combining self-efficacy training, action planning, and personalized use goal setting, in a 20-day randomized controlled trial. When compared to standard methods, these interventions achieved similar reductions in screen time but yielded significantly higher gains in users' self-regulation and sustained positive habits [7]. Another study published the "Time 2 Stop" app, which showed that the provision of self-regulation support systems assists users in the monitoring of problematic smartphone usage and the reflection on their patterns through prompts and visualizations linked to personal goals [14].

2.2 Conversational Agents for Self-care and Behaviour Change

Conversational agents (CAs), rule-based chatbots and LLM based systems, are being adopted more frequently to support self-care by providing personalised dialogue, adaptive feedback, and user engagement.

Kocielnik et al.[8] introduced Reflection Companion, a CA that prompts users to reflect on their physical activity via daily mini-dialogues paired with activity graphs. However, it focuses solely on physical activity and does consider other aspects of behaviour change.

The advent of LLMs has enabled more sophisticated, context-aware interventions. MindShift [20] leverages LLMs to generate personalized persuasive messages based on app use, inferred mental states, and user goals, demonstrating reductions in smartphone use and higher intervention acceptance. LLM based interventions have been applied in the detection of stress by combining data from wearable sensors, with the objective of detecting stress events in real time. This detection triggers a LLM chatbot to deliver personalized stress management interventions.

LLM are also being used to gain a deeper understanding of user states. Zhang et al. [22] demonstrated the efficacy of LLMs in predicting affective outcomes and general well-being from smartphone data. In the realm of physical activity, GPTCoach [6] demonstrate how LLM based systems that incorporate wearable data and motivational strategies can create personalized activity plans by gathering rich qualitative information about a user's context to tailor support.

2.3 Proposed contribution

Most existing smartphone sensing studies focus mainly on pattern detection or alert driven intervention, rarely incorporating reflective feedback loops connect sensed behaviours with user goals. This work addresses this gap by integrating a passive sensing infrastructure with personalized goal setting, and conversational feedback powered by LLMs. Specifically, we leverage AWARE-Light's capabilities to passively collect fine-grained smartphone usage data. This data then informs an LLM-based conversational agent designed to prompt users for daily self-reflection, explicitly connecting their observed smartphone behaviours with their personal objectives and sensed data patterns over time. This approach enables adaptive conversational feedback based on whether user behaviour aligns with or deviates from their stated goals and perception of progress. It moves beyond merely delivering information to actively encourage self-awareness and nudge users towards meaningful behaviour change. Notably, the initial prototype of this system was developed rapidly over 4-5 days at the UBISS summer school[1], underscoring the practical feasibility of integrating sensing frameworks like AWARE-Light rather than building stand-alone apps for each study. While this work represents an early-stage proof-of-concept, it highlights the potential for tools that support self-awareness and digital well-being through the combination of real-time behavioural data and personalized LLM driven dialogue.

3 SYSTEM OVERVIEW

This system integrates passive smartphone sensing, self-reported reflection, personalized goal setting, and LLM-assisted feedback to help users improve self-awareness and behaviour alignment with their goals.

Figure 1 presents a user's daily journey. The process begins each morning with the user setting a specific goal. Throughout the day, the system passively collects smartphone usage data via AWARE-Light. The user is prompted to complete brief reflections throughout the day to encourage alignment with their stated goals. At the end

[1]13th International UBI Summer School Oulu, Finland, June 9-14, 2025. Webpage: https://ubicomp.oulu.fi/ubiss2025

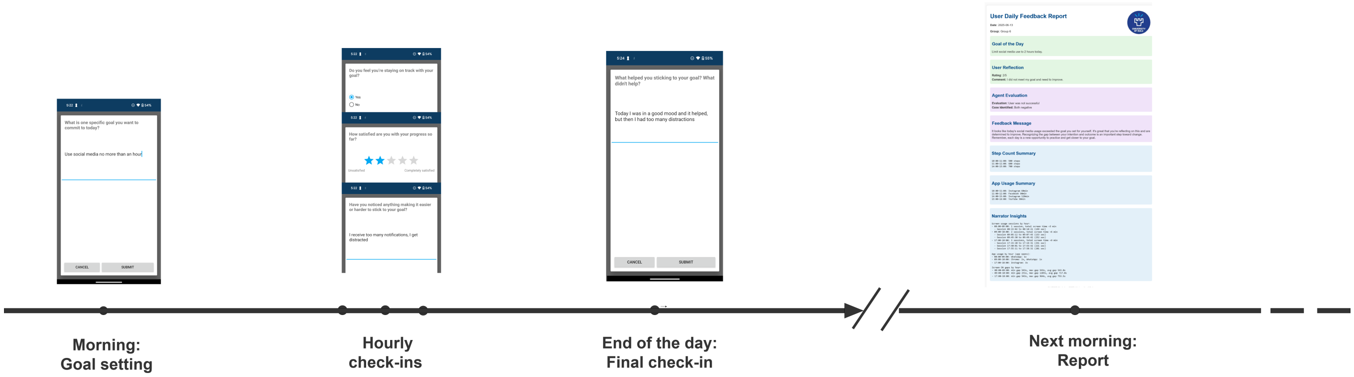

Figure 1: User journey

of the day, the user is prompted to give an overall review of the day.

After the final review, the user's data and self reflections are summarised by the back end and compiled into a a prompt that is sent to the OpenAI API[2]. The response form the API is then used to compile an HTML report that is presented to the user the next morning.

3.1 System Architecture

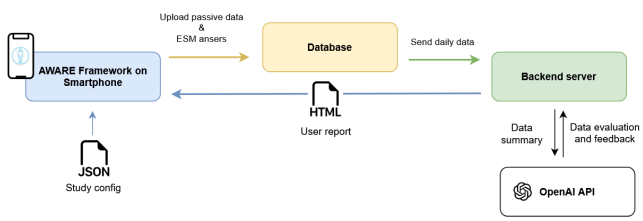

Figure 2: System Architecture overview

Figure 2 shows the high-level system architecture. The AWARE-light mobile app collects sensor data and Experience Sampling Method (ESM) responses. The full list of sensor data we can be seen in Table 1. This data is sent to a hosted MySQL database, which acts as the central repository for sensor events and user self-reports. The back end data pipeline processes incoming sensor data to produce structured summaries of daily smartphone behaviour and physical activity. The system integrates user self-reports, including daily goal-setting and end-of-day reflections, with the processed sensor data. This combined data is then compiled into a structured text prompt. The prompt is passed to the OpenAI API, along with an agent prompt. The API returns an LLM-generated feedback. The back end system renders this output as an HTML report, designed to be shown to the user the following day. The report highlights in different colours the different types of data, so the user clearly knows which content is programmatically generated and which is produced by the LLM.

[2]OpenAI API allows programmatic access to OpenAI recent models. Website: https://openai.com/index/openai-api/

Table 1: Sensors used in study

Sensor	Description	Sampling Frequency
Applications Foreground	Detects which app is active	30 seconds
Applications Notifications	Captures incoming notifications	Event-based
Battery	Monitors battery state and events	Event-based
Accelerometer	Measures 3D acceleration	20000 Hz
Gravity Sensor	Measures gravity-excluded acceleration	20000 Hz
Bluetooth	Detects nearby Bluetooth devices	60 seconds

3.2 Data Processing Pipeline

To provide personalized feedback, our system employs a data processing pipeline, visualised in Figure 3, that transforms raw smartphone sensor data and user self reports into structured inputs for the LLMs. Data collection begins with the AWARE-Light smartphone application, which passively gathers a wide array of sensor data and sends them to a hosted MySQL database. Data from accelerometer and gravity tables are combined to derive daily step counts. `Screen` and `applications_foreground` data are processed to generate granular app usage summaries, detailing application activity by time intervals (e.g., "10:00-11:00: Instagram 15min, 11:00-12:00: Facebook 25min").

`Applications_foreground`, `applications_notifications`, `battery`, and `bluetooth` are fed into the AWARE Narrator tool[3]. This tool converts raw sensor data into a human-readable, event-based log. The Narrator tool reduces verbosity of the logs, but the output remains extensive. A custom summary script is used to further condense the Narrator logs into a concise, hourly overview of screen usage sessions, app opens, and screen ON gaps, resulting in a lower

[3]The AWARE Narrator tool converts AWARE data records into English statements that describe the records. Website: https://awareframework.com/aware-narrator/

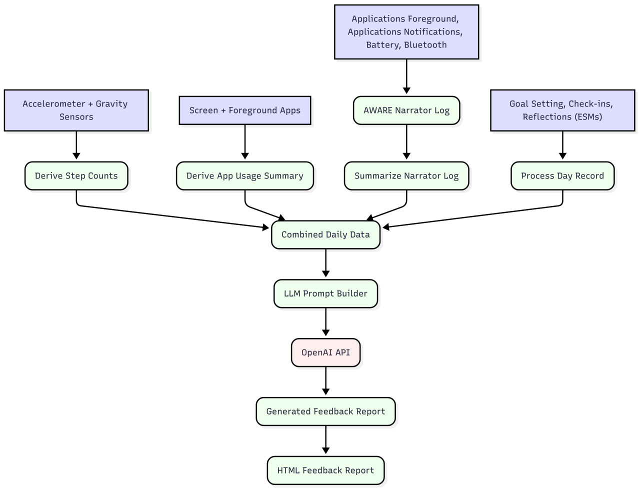

Figure 3: Data Processing Pipeline Diagram

token count that is suitable for LLM consumption.
The user self-reported data collected via ESMs is integrated into a structured day record object, encapsulating the user's stated goals, daily progress, and reflections.
Finally, all these derived data streams are combined to form the comprehensive LLM prompt. This rich, contextualized input allows the LLM to generate personalized and adaptive feedback.

3.3 LLM Feedback Generation

The prompting process, consists of two main elements: the Agent Prompt and the Action Prompt.
Agent Prompt defines the LLM's persona, tone, and coaching style. It incorporates behavioural science principles; specifically Goal Setting Theory, ERG Theory (Existence, Relatedness, Growth), and behavioural nudging, by explicitly referencing them in the system prompt. Rather than crafting detailed prompt logic for each principle, we relied on the LLM's pretrained understanding to interpret and apply these principals. This is a lightweight and flexible approach, that leverages the theories without extensive prompt engineering. In addition, the experience sampling questions delivered throughout the day served as another source of subtle nudges to the user.
Crucially, we also introduced an evaluation matrix, shown in Table 2, which instructed the LLM on how to tailor its feedback based on the alignment between the user's self-reported reflections and the objective behavioural data.

The **Action Prompt** combines several key data points: the user's daily goal, their self-reported reflections on progress and satisfaction, the objective app usage data aggregated by hour, hourly step counts, and a summarized Narrator log detailing screen usage sessions and app opens. An illustrative example of the data structure provided to the LLM within the Action Prompt is shown in Figure 4. The combined Agent and Action prompts are then sent to the OpenAI API. Based on the provided data and the guiding principles, the LLM is instructed to return a structured response that is then

Table 2: Evaluation matrix comparing user reflection and sensed behaviour alignment

	Agent Evaluation: Positive	Agent Evaluation: Negative
User Positive	Reinforce success	Prompt reflection
User Negative	Encourage confidence	Suggest improvements

User Goal:
Limit social media use to 2 hours today.
User Reflections:
Success rating: 2/5
Comment: I did not meet my goal and need to improve.
App Usage (by hour):
10:00-11:00: Instagram 60min
11:00-12:00: Facebook 90min
14:00-15:00: Instagram 120min
15:00-16:00: YouTube 30min
Step Counts (by hour):
10:00-11:00: 500 steps
11:00-12:00: 600 steps
14:00-15:00: 700 steps
Narrator Summary:
Screen usage sessions by hour:
- 08:00-09:00: 1 session, total screen time 3 min
... (further summarized screen usage, app opens, and screen ON gaps) ...

Figure 4: Example of the Action Prompt.

parsed by our system. This raw LLM output includes: (1) **Agent Evaluation**: A categorization of the user's self-perception against objective data, directly referencing the evaluation matrix. (2) **Feedback Message**: The core personalized text, formatted as a natural language message designed to provide motivation, foster reflection, or offer gentle nudges.(3) **Suggested Strategies**: Actionable tips or recommendations directly relevant to the user's goal and observed behaviour.
An example of this structured LLM response, specifically for a scenario where the user's reflection and objective data were both negative regarding their goal, is shown in Figure 5.

Upon receiving this structured response, our system combines these elements with other static and dynamic information into a final, user-facing HTML report, shown in Figure 1. This HTML formatting allows for a clear and visually appealing structure, enabling potential interactive highlights of relevant data points and embedding visually distinct, goal-relevant prompts directly within the report. The colour coding makes it clear to the user which elements are sensor-based, generated by the LLM, or provided by the user.

1. Agent Evaluation
User was not successful in limiting social media usage to 2 hours.
This is a case of *Both negative*.
2. Feedback Message
It looks like today's social media usage exceeded the goal you set for yourself. It's great that you're reflecting on this and are determined to improve. Recognizing the gap between your intention and outcome is an important step toward change. Remember, each day is a new opportunity to practice and get closer to your goal.
3. Suggested Strategies
1. **Set Specific Break Times**: Schedule specific times during the day when you allow yourself to check social media, and use a timer to stick to it. This can help prevent extended, unplanned usage.
2. **App Tracking and Alerts**: Use built-in features on your smartphone or third-party apps to alert you when you've reached your self-imposed daily limit on social media usage. This can increase awareness and help you stay within your limits.

Figure 5: Example of the Agent response.

3.4 Rapid Development Context

This system was developed as an early-stage proof-of-concept over an intensive 5 day period at the UBISS 2025 summer school. The workshop was based around the use of AWARE-Light for passive smartphone sensing, thus significantly reduced the need for extensive custom mobile application development, allowing for quick deployment across platforms. Similarly, the use of commercial LLM APIs streamlined the implementation of the feedback mechanisms. This approach underscores the feasibility of rapidly prototyping context-aware behavioural interventions by assembling modular components.

4 FEASIBILITY TESTING WITH GENERATED DATA

To evaluate the system's ability to generate goal aligned feedback, we tested the data processing pipeline using generated test scenarios. These scenarios cover the combinations of user self-reported perceptions and objective sensor data, simulating key alignment and misalignment cases shown in Table 2. All the data used for the tests was hand made, based on samples collected by the authors through the AWARE framework.
Table 3 shows the result from these four test cases. We found that in all four cases, the agent was able to identify the correct alignment case and replied with an appropriate, expected response.

To illustrate the LLMs ability to generate personalised feedback, we present two representative excerpts from the generated test scenarios:

Table 3: LLM Evaluation Results Across Test Scenarios

Alignment	Expected Response	LLM Evaluation
Both Positive	Reinforce Success	Correct
Both Negative	Suggest Improvements	Correct
User Positive, Data Negative	Prompt Reflection	Correct
User Negative, Data Positive	Encourage Confidence	Correct

> "It seems like you feel positive about your progress, which is great! However, the data indicates that your smartphone usage exceeded your 3-hour daily goal, especially in the afternoon. Recognizing these patterns is a strong first step, and it's fantastic that you're aware of areas for improvement. Consider focusing on reducing screen time in specific high-usage hours."

This response reflects a case where the user's perception was positive, but the observed behaviour did not align with their goal. The LLM provided constructive feedback, reinforcing self-awareness while gently prompting reflection on specific high-usage periods.

> "You've done a great job managing your social media usage today, staying well under your 2-hour limit with only 85 minutes spent on Instagram and Facebook. It's important to recognize these successes, as they indicate that you're effectively moderating your social media habits. Keep up the good work and continue building on this positive momentum! "

Here, the LLM adapted the feedback to encourage confidence, acknowledging the misalignment between the user's negative self-perception and the objectively positive behavioural outcome.
The system generates actionable strategies to help the user align their behaviour with their goals. For the scenario where the user's perception was positive, but their observed behaviour exceeded the target, the following suggestion was provided:

> "1. **Set Specific Break Times**: Schedule short, intentional breaks from screens during high usage periods in the afternoon to reduce overall screen time."

The feasibility testing demonstrates that the system can process simulated behavioural data and user reflections to generate personalised feedback aligned with our evaluation matrix. In all test cases, the LLM produced supportive, context-aware responses and actionable suggestions where relevant. While these results are promising, they reflect early-stage testing with generated data, and further evaluation with real-world user studies is needed to validate effectiveness and generalisability.

5 DISCUSSION AND FUTURE WORK

This work presents a proof-of-concept system that integrates passive smartphone sensing, personalised goal setting, and LLM-generated reflective feedback to promote self-awareness around user goals. Our feasibility testing demonstrates the system's ability to combine self-reported perceptions with objective sensor data to generate feedback aligned with behavioural change coaching principles.

However, the system remains at an early stage. The current evaluation was conducted using simulated data derived from real-world samples, and no in-the-wild deployment has occurred yet. The feedback generation process relies on pre-configured LLM prompting, which requires further refinement to ensure consistent relevance, clarity, and user acceptance.

Privacy was not a core focus of this rapid prototype, but it will be to future iterations. Integration with the CARP framework will support secure data handling and informed consent. However, the current reliance on the OpenAI API introduces additional privacy considerations. We will either require transitioning to a self hosted LLM solution, or explicitly addressing the use in the consent process.

Future development will transition to using the CARP mobile sensing framework, providing greater cross platform capabilities compared to AWARE, which was used as a requirement for the UBISS summer school. Next steps include: (1) Conducting real-world user study to evaluate usability and impact on self-awareness and behaviour alignment. (2) Improving the LLM prompting strategy to support a broader set of goal setting. (3) Expanding the system to incorporate additional sensing modalities available via CARP. (4) Generalising the data processing and feedback pipeline to support broader behavioural change applications.

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