Typing Patterns as Digital Footprints: Enhancing Health Monitoring

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Abstract

In today's world, digital devices have a central role in the daily routine, being widely used for communication, work and leisure. The data created while interacting with these devices, known as digital footprints, can reveal patterns and behaviours that can be leveraged for health monitoring. Most tasks performed on digital devices, such as smartphones, involve typing text, which requires motor skills and cognitive functions. Previous works have been assessing typing behaviours and associating them with disease early detection, such as Parkinson's disease, bipolar disorder and Alzheimer's disease; and health states, such as fatigue and stress, with text-entry data predominantly collected in controlled conditions. However, these controlled environments might impact the typing patterns, failing to accurately represent the real-world settings. Therefore, assessing keystroke dynamics for health monitoring requires a shift from conventional in-the-clinic studies to in-the-wild assessments. In this work, we reflect on the potential of WildKey, a privacy-aware keyboard that collects text-entry data in the wild, as a digital footprint for health monitoring and disease detection. We also discuss the opportunities and challenges of digital footprints, namely their potential for continuous and reliable monitoring, and the associated privacy and ethical concerns.

CCS Concepts

• **Human-centered computing → Smartphones**.

Keywords

text-entry, typing, health monitoring, digital footprints

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1 Introduction

The increasing use of digital technologies, such as smartphones, has generated a large volume of data in our daily lives, opening new opportunities to leverage the collected data for non-invasive and continuous health monitoring. Collected digital data, also known as digital footprints, can be used to identify behavioural patterns, emerging as valuable health digital biomarkers. Indeed, smartwatches and smartphone applications have been extensively used to track health-related metrics, such as physical activity, fertility, and blood glucose levels [21]. Additionally, data extracted from social media, particularly Twitter activity timing, has been shown to predict both mental well-being and sleep quality [11].

Digital footprints are divided into two main categories: passive, when data is collected in the background without the user's input; and active, when a user intentionally shares information. Web-tracking technologies (website cookies), search engines (browsing history), social media, tracking technologies (geolocation, wearables, health logs), and text-entry (keystroke dynamics) are examples of technologies that act as digital footprints.

Among these different types of digital footprints, text-entry behaviour data emerges as a promising source of data in the health context. Typing is one of the most frequent tasks when using digital devices; namely, when using search engines, writing an email, typing notes and tasks, exchanging text messages, and interacting on social media. Moreover, typing involves both coordinated and repetitive motor skills, as well as a high level of cognitive functions. In fact, individuals with low global cognition possibly related with Alzheimer's disease were observed to be slower writers and to take more time to correct errors and initiate the next word [12]. Therefore, assessing a person's typing behaviour on digital devices, such as typing speed [14], errors [18] and touch dynamics [3], can reflect a person's motor function and cognitive state, creating a digital footprint with high potential as a health digital biomarker.

Wearable devices have been used to identify disease symptoms; however, since several diseases affect motor and/or non-motor functions, leading to a negative impact on typing performance, keystroke dynamics analysis in common devices, such as smartphones, was proven to be a good alternative to those dedicated wearable devices. Typing metrics have been used as digital biomarkers in disease early detection [3, 9, 12, 13, 20, 25, 26] and to assess health states [1, 6, 15].

Most health monitoring systems still rely on self-reported data and physical activity tracking, overlooking the valuable insights provided by everyday typing patterns. In this work, we explore the potential of text-entry data as a digital biomarker for health monitoring, highlighting the role of WildKey, a privacy-aware keyboard designed for real-world data collection. We showcase WildKey's potential in two health monitoring case studies: IDEA-FAST and COTIDIANA. Additionally, we discuss the opportunities and challenges of exploring text-entry as a digital biomarker in health monitoring, particularly its advantage over traditional monitoring approaches and as a source of continuous and real-world data, as well as the concerns regarding user privacy and data usage.

2 Related Work

The growing adoption of digital technologies, including smartphones, has led to the generation of vast amounts of data in our daily activities. Digital footprints, i.e. the data created by a person while interacting with electronic devices and using the internet, can reveal a person's behaviours and lifestyle. Leveraging this data has become a hot topic in multiple research fields, namely in health, enabling a data-driven approach to individual and public health monitoring. Compared to the traditional in-clinic monitoring methods provided by healthcare professionals, digital devices have the advantage of collecting data that can characterise a person's health status in a continuous, non-invasive and quantitative way. Digital footprint data can arise from multiple technologies; for example, previous research has demonstrated the potential of social media usage in tracking mental health behaviours [5, 11]. Furthermore, online activity or supermarket transactions have also been demonstrated to provide insights into the emotional state, treatment adherence, and symptom progression of cancer patients, since purchases of pain and indigestion medication acted as an early indicator of ovarian cancer [4]. Moreover, medication sales data were also integrated into respiratory disease forecasting models [8].

Text-entry data also stands out as a promising technology in health monitoring and research, as typing patterns reflect motor abilities and cognitive functions. Previous research has explored the analysis of text-entry metrics, such as typing speed [14], errors [18] and touch dynamics [3], for health applications. Studies have shown that keystroke dynamics can be used as digital biomarkers in multiple disease conditions, such as Parkinson's disease [2, 3, 7, 9, 25], bipolar disorder [26], mild cognitive impairment [20], multiple sclerosis [13] and Alzheimer's disease [12], revealing the huge potential of text-entry data for early detection and monitoring. Besides the proven potential in disease detection, text-entry data has also been used to assess health states, such as stress [6], fatigue [1] and inebriation [15]. Moreover, combining keystroke dynamics with other data sources might provide better models. The combination of accelerometer data while typing and keystroke dynamics have been explored to provide a more comprehensive understanding of brain functioning than only using the keystroke dynamics alone [19].

Despite the demonstrated potential of text-entry data as a health digital biomarker, most approaches are based on controlled environments, restricting their application in the real-world. Previous research showed that typing performance varies between control conditions and real-world settings, suggesting that laboratory studies may not represent everyday typing patterns [18, 22]. Therefore, assessing keystroke dynamics for health monitoring requires a shift from conventional in-the-clinic studies to in-the-wild assessment. Several approaches for data collection in the wild have been developed, including prompting users to perform specific typing tasks or passive collection of typing metrics such as flight and hold times. Those approaches have limitations and depending on the situation a combination of those might be the right solution. For this reason, the WildKey toolkit was developed by our group to combine both prompted tasks and passive data collection, without storing any raw text data [24].

3 WildKey as a potential health monitoring tool

The WildKey toolkit is an open-source and privacy-aware keyboard toolkit designed to collect data in both implicit (passive sensing) and explicit (prompted tasks) ways in the wild [24]. This allows people to monitor their health through both the day-to-day usage of their devices and/or by performing specific sampling tasks. As a regular keyboard, WildKey can analyse all written text despite the application a person is using. Moreover, we follow a privacy-by-design approach, as no textual content is stored or shared. Collected metrics include words per minute (the number of words written by the user per minute), flight time (time taken between characters), hold time (time pressing a key), corrected error rate (percentage of corrected errors), uncorrected error rate (percentage of uncorrected errors) and total error rate, among others [24].

We have been exploring the WildKey toolkit in various projects to evaluate its potential use in health monitoring. In previous work, Rodrigues et al. [23] assessed the trade-offs of everyday text-entry collection methods using WildKey. Wildkey supports both experience sampling, where users can engage in four types of prompts (transcriptions, compositions, questionnaires, and custom-made tasks), and passive sampling, where all text-entry actions are analysed regardless of the application in use. The study found that typing performance and behaviours vary both between and within experience sampling and passive sensing. For example, passive sensing is better suited for long-term data collection, as participants are less likely to use experience sampling for long periods, and passive collection does not require additional effort. On the other hand, participants generally performed better in experience sampling. Therefore, the choice of collection method should be guided by the context of the experimental design [23].

More recently, Matias et al. [16] used the WildKey in the creation of the COTIDIANA dataset, an open-access resource that combines smartphone-collected data on mobility and physical activity, finger dexterity, and mental health in Rheumatic and Musculoskeletal Diseases. Keystroke dynamics data collected with the Wildkey was integrated into the Keyboard Sentence Transcription (KST) activity together with the smartphone's IMU sensors, giving insight into fine motor function. Results showed that keystroke-related variables (e.g., flight time) were associated with the performance of the fine motor skill assessment test, highlighting WildKey's potential as a monitoring tool.

Furthermore, we are also exploring the WildKey keyboard as a potential digital biomarker within the IDEA-FAST project [10]. This project evaluates multiple digital health technologies, including the WildKey keyboard, in home settings to identify digital endpoints that provide objective, sensitive, and reliable assessments of fatigue and sleep. The aim is to enhance the treatment of symptoms in neurodegenerative and inflammatory diseases, with the help of everyday data collected seamlessly. So far, we have been exploring the typing behaviours across cohorts and concluded that participants with Parkinson's disease are slower writers, i.e., write fewer words within a minute, and take more time changing keys (higher flight time). We also observed that demographic characteristics (age and gender), time of the day when a person writes and motor abilities affect the typing performance (words per minute and flight time) of patients with Parkinson's disease, revealing the importance of including these covariables in future prediction models.

So far, studies suggest that everyday text-entry data collected by WildKey holds significant potential as a digital footprint in health monitoring, providing insights into cognitive and motor performance. Moreover, these studies also highlight WildKey's potential as a continuous and non-invasive tool in day-to-day life for assessing health conditions in real-world environments.

4 Opportunities and Challenges

In this highly technological era, where smartphones and other digital devices are an essential part of everyday life, digital footprints, such as text-entry patterns, offer valuable possibilities across multiple areas. In healthcare, they can be explored as digital biomarkers for disease early detection, personalized healthcare and overall well-being, supporting data-driven medical approaches. Traditionally, health monitoring relies on active participation, requiring individuals to complete self-reports, undergo clinical tests, and attend medical appointments. This introduces a certain bias, as data collection depends on a person's availability. On the other hand, **digital footprints enable continuous, real-world data collection** with minimal effort, providing a more objective view of a person's health. However, **in-the-wild data collection is often incomplete and noisy**, requiring careful preprocessing and interpretation. To have an effective value, raw digital footprint data must be meaningfully integrated with clinical knowledge.

Despite providing valuable insights into a person's health state, digital footprints should not be seen as a replacement for medical diagnosis. They can serve as an **additional source of information** that patients can bring to clinical appointments, acting as a detailed backlog of their health over time. In this way, data could help medical professionals in tracking patients' symptoms and adjusting treatments accordingly. Furthermore, **digital footprints enable remote monitoring**, allowing early intervention measures, especially for patients in remote areas. Nevertheless, users' perception of the symptoms might be influenced by the data, so it should be presented to the patients with care. Moreover, it is also important to evaluate the impact of digital devices on daily routine to select the best digital footprints. If a device negatively impacts daily life, whether by being uncomfortable to wear or difficult to use, it might discourage long-term use, compromising the goal of continuous monitoring. Integrating multiple digital biomarkers could also improve the accuracy of health assessment. For instance, providing contextual data, such as activity data and time of day, could enhance the interpretation of behavioural patterns like typing, leading to more precise models.

While promising, the use of text-entry metrics and other **digital footprints raises several challenges and concerns regarding privacy and data security**. In text-entry studies, these concerns have been addressed and data collection tools were designed not to capture any typed text or data that allow its reconstruction, as well as the used applications, preserving the users' anonymity [24, 25]. Furthermore, users' awareness that no raw data is being gathered enhanced their confidence in using text-entry data collection tools [23]. Therefore, maintaining transparency and providing data security might facilitate users' consent for data collection.

The use of digital footprints has also raised ethical concerns, especially during the COVID-19 pandemic. In several countries, governments have used digital footprints to control the spread of the disease, disclosing patients' information and violating privacy [17]. Legal frameworks and political support are essential to regulate the use of data without jeopardising individuals' safety. Policy-makers play a vital role in ensuring the necessary legal frameworks and political support are in place to facilitate the effective use of data, and as such, it's important to continue to engage these key stakeholders in the conversation.

5 Outlook

With the widespread of digital technologies, the role of digital footprints is expanding to multiple fields. As discussed in this work, digital footprints have become an increasingly valuable tool in health monitoring. Text-entry data, in particular, has the potential to act as a continuous and non-invasive health-associated metric, providing insights into health states and disease conditions. Advancements in artificial intelligence and machine and deep learning models will enable the development of models with better performance and accuracy. As digital footprints became widely used, questions about data ownership and privacy are raised, since users are often unaware that personal data is being collected and shared. Ensuring user consent and data collection transparency and privacy is crucial to the future of digital footprint in healthcare.

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