

Ubiquitous digital health-related data: clarification of concepts

Erlend Johannessen¹, André Henriksen¹, Gunnar Hartvigsen^{1,2}, Alexander Horsch¹, Eirik Årsand¹, Jonas Johansson³

¹Department of Computer Science, UiT, The Arctic University of Norway, Tromsø, Norway, erlend.johannessen@uit.no

²Department of Health and Nursing Science, University of Agder, Grimstad, Norway

³Department of Community Medicine, UiT, The Arctic University of Norway, Tromsø, Norway

Abstract

The increased development and use of ubiquitous digital services reinforce the trend where health-related data is generated everywhere. Data usage in different areas introduces different terms for the same or similar concepts. This adds to the confusion of what these terms represent. We aim to provide an overview of concepts and terms used in connection with digital twins and in a healthcare context.

Keywords

Digital Twin, Digital thread, Digital shadow, Small data, Terms and concepts, Healthcare

1 INTRODUCTION

Traditionally the healthcare field has been subject to strict privacy regimes. Patient data has only been available to health personnel with privileges to view or use this data. Details describing health conditions and health history has been and is still regarded as a matter between doctor and patient.

The development and use of ubiquitous (ever-present) digital services, online or offline, is based on the increasing trend that health-related data is generated “everywhere”. These types of data would not specifically describe the person that is using the digital services collecting these data. But when assembling various types of data for an individual, this may create a “customer” profile that can form identifying characteristics of the person. When assembling all available data for a person, we are approaching the concept of a digital twin.

A digital twin is generally defined as a digital replica of a living or non-living physical entity. The term digital twin was first presented by Michael Grieves in 2002-2003, and published in a white-paper in 2014 [1]. The term has been used in the manufacturing industry for over a decade with the aim of minimising costs, improving quality and product life, and increase efficiency in manufacturing. The concept of virtualising physical entities has since spread into other areas such as business, education, healthcare, transport, and construction.

Roberto Saracco’s article *Digital Twins: Bridging Physical Space and Cyberspace* [2] discusses the impact of digital twins and some future challenges. He defines a digital twin as consisting of a digital model, shadow, and thread. He predicts that digital twins will be applied to people in a not-too-distant future.

One problem with the concept of digital twins is that many of the terms in the digital twin field are used as synonyms. In her 2020 post [3], Lindsey Andrew argues that the term digital twin has become a buzzword, through the hype of

what can be provided versus the reality of the actual solutions. She also suggests that the term is overused and creates unrealistic expectations for the use of digital twinning. The fact that a search for “digital twin” today will result in millions of results [4] supports the hypothesis that we are witnessing a hype around the “digital twin” concept.

There are several other terms that are used alongside the term digital twin. All these terms are used under similar circumstances. To some degree they are used as synonyms, adding further to the confusion around the precise semantics of the underlying concepts. In order to be able to utilise these terms and concepts in a healthcare context, we need to clearly define them.

The aim of this paper is to provide an overview of concepts and terms used in connection with digital twins and define them in a healthcare context.

2 METHOD

The database Web of Science was searched with the queries "digital dust", "digital footprint", "digital phenotype", "digital shadow", "digital thread", "digital traces", and "small data". The goal with the search was finding explanatory articles, literary reviews, and scoping reviews where these and related terms were defined. The search query "digital twin" was expanded to "*digital twin*" AND ("*literature review*" OR "*scoping review*") to limit the results to more relevant articles.

We summarised number of papers for each search terms in a table in order to try to identify the most used concepts. The uncovered documents were skimmed for relevant articles, focussing on studies that could help explain digital twin related concepts and terms. Non-English and duplicate studies were excluded from the results.

3 RESULTS

An overview of the results from the term search can be seen in Table 1. A total number of 3727 studies were found, after

The 18th Scandinavian Conference on Health informatics, Tromsø, Norway, August 22-24, 2022. Organized by UiT The Arctic University of Norway. Conference Proceedings published by Linköping University Electronic Press at <https://doi.org/10.3384/ecp187>. © The Author(s). This work is licensed under the Creative Commons Attribution-NonCommercial 4.0 International License. To view a copy of this license, visit <http://creativecommons.org/licenses/by-nc/4.0/>

removing duplicates (n=223) and studies in other languages than English (n=50).

Some of these terms were already found in Roberto Saracco’s digital twin article [2] mentioned in the introduction. Especially the Semeraro et al. article *Digital Twin Paradigm: A Systematic Literature Review* [5] was useful, in that it listed 30 different definitions of what a digital twin is.

Term searched for	Results
Behavlets	1
Digital dust	4
Digital footprint	259
Digital phenotype	56
Digital shadow	73
Digital thread	103
Digital traces	427
Digital twin scoping/literature review	99
Small data	2705

Table 1. Results from literature search

Four articles in particular is worth mentioning with regard to definition and discussion of concepts.

The 2020 article *Digital Twins and the Emerging Science of Self: Implications for Digital Health Experience Design and “Small” Data* by Schwartz et al. [6] divides publicly available health data into four categories, 1) clinically generated data, 2) commercial real-world health data, 3) consumer digital health device-generated data, and 4) health-suggestive data. They also discuss the renaissance of N-of-1 or individual science. N-of-1 evaluation creates the opportunity to evaluate each individual uniquely.

Jones et al. [7], in their study *Characterising the Digital Twin: A systematic literature review*, defined 13 characteristics of digital twins, Physical Entity/Twin; Virtual Entity/Twin; Physical Environment; Virtual Environment; State; Realisation; Metrology; Twinning; Twinning Rate; Physical-to-Virtual Connection/Twinning; Virtual-to-Physical Connection/Twinning; Physical Processes; and Virtual Processes, and a framework with regard to digital twin operation. They also identified topics for future research.

Househ et al. [8], in their writeup *Big Data, Big Problems: A Healthcare Perspective*, argues that small data can be more accurate and can bring about more improved healthcare outcomes than big data systems, and that big data may cause more problems than solutions for healthcare.

In their article *Digital Twin in manufacturing: A categorical literature review and classification*, Kritzinger et al. [9] define digital twin, digital model, and digital shadow in more detail, to clear up any confusion around these terms.

4 TERMS AND CONCEPTS

This chapter outlines the terms searched for, and in addition some other terms that are interesting in a health-related

context. The terms in this chapter are divided into terms which originates in the industry and is not necessarily health-related, and those terms that are directly connected to human use of digital devices and services.

4.1 Terms used in an industrial context

The term digital twin is used in many different contexts and has been used to describe dissimilar scenarios. One problem is that the terms digital twin, digital model, and digital shadow often are used interchangeably. Other synonyms used for these include computerized counterpart, digital avatar, digital copy, digital replica, digital representation, dynamic virtual model, living model, virtual model, virtual prototype, and virtual replica. This usage may or may not include data transfer between the physical and digital entity. A summary of these terms can be found in Table 2.

Digital model

A digital model could be described as a representation of a physical entity. Digital models could be e.g., simulation models of planned entities or mathematical models of already existing entities. There is no automated data exchange between the physical entity and the digital model [9]. The dotted line in Figure 1 signifies this initial and/or manual updates.

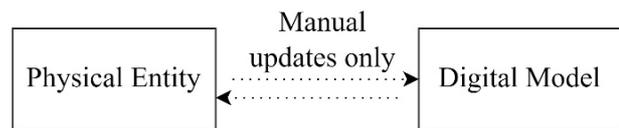


Figure 1. Digital model with initial and/or manual updates only

Digital shadow

If there exists an unidirectional flow of data from the physical entity to the digital model, then this could be defined as a digital shadow [9], visualised in Figure 2. The dataflow originates in changes of the physical entity as e.g., measured by sensors in the entity, and then creates changes to the digital model. Changes to the physical entity would happen through manual updates only.

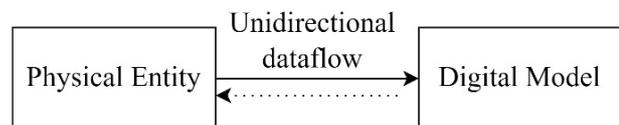


Figure 2. Digital shadow with unidirectional dataflow to update the digital model

Digital twin

If there exists a two-way data flow between the digital model and the modelled physical entity, this can be referenced to as a digital twin. In this case the data from the digital twin may control or update the physical entity, and vice versa, see Figure 3. Other related digital or physical systems or entities may control or update the paired entities, digital and physical [9].

Term	Categories	Description / Explanation	Example
Digital model	Data, Infrastructure	A digital representation of a physical entity	Having a computer-aided design (CAD) model of a building.
Digital shadow	Data, Process, Infrastructure	A digital model, where changes to the physical entity updates the digital model continuously (in real-time)	Updating the digital model with data from the actual physical construction in real time.
Digital thread	Data, Process, Infrastructure, Time	A data-driven architecture that links all information generated and stored within the digital twin, enabling it to flow seamlessly through the entire lifetime of the physical entity from invention to disposal	Logging events in the mechanisms and state of the building in order to analyse its history, to make it more efficient in the future, or to predict when to do maintenance.
Digital twin	Data, Process, Infrastructure	A digital model, where changes to the physical entity updates the digital model continuously (in real-time), and vice versa	Measuring changes to the building, updating the digital model, and automatically implement changes to the physical building based on the current state.

Table 2. Terms originating in the manufacturing industry

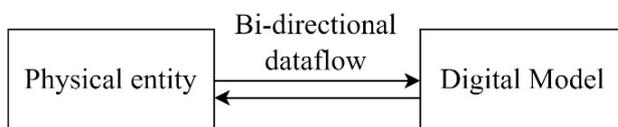


Figure 3. Digital twin with bidirectional dataflow to update both digital model and physical entity

The concept of creating or using a digital twin in order to optimise and maintain the underlying physical entity or process is also referred to as *digital twinning* [10].

Digital thread

A digital thread is recording or logging of a digital entity's lifetime, from creation to termination. Digital threads in smart manufacturing aim to show the physical entity's changes throughout its lifespan by following a product's design, performance data, product data, supply chain data, and software [11].

4.2 Terms used in a human context

There are several terms that arise from a human using digital services. This section describes most of them. A summary can be found in Table 3.

Digital traces

Digital traces (or digital trace data) are data we share when using digital devices, actively or passively [12]. As opposed to physical traces, like footprints in the sand, digital traces are the digital "footprints" we leave behind when using technical systems such as websites, social media platforms, smartphone apps, and sensors. Some of these traces are intentional, like emails, texts, blog posts, tweets, comments or likes on social media sites like Twitter and Facebook. However, many traces are invisible and unintentional, like records of our website visits and searches, or global-positioning systems (GPS), logs of movements, or phone calls.

Digital dust

Another term used as a synonym for digital traces may be digital dust [13]. This term is used in connection with online use and behavioural digital traces, see also *The Internet of Behaviour*, described below.

This term, however, has not yet been confirmed as a scientific term. It is used in several different ways in research, sometimes casually; what's left online when people die [14], digital investigation (forensics, defence) [15], criminal investigation [16], or grey literature (literature like presentations, reports, blogs, papers, produced outside traditional publishing channels) [17].

Small data

Small data is derived from our individual digital traces. Consider a new kind of cloud-based app that would create a picture of your health over time by continuously, securely, and privately analysing the digital traces you generate as you work, shop, sleep, eat, exercise, and communicate.

While there are personal devices and Internet services specifically designed for self-tracking, digital traces include a much richer corpus of data that we generate every day [18].

Digital phenotype

A digital phenotype, as defined by Jain et al. [19], can be regarded as a term for the trail of relevant health data that are left behind in people's use of the internet, social media, and digital technologies in general. Jain argues that this data largely is an untapped potential for early detection of various health conditions.

Digital phenotyping is a term introduced by Tourus et al. [20], and is described as "moment-by-moment quantification of the individual-level human phenotype in-situ using data from smartphones and other personal digital devices". Tourus et al. defines digital phenotyping as distinct from the term digital phenotype. Their goal was creating a platform to collect research-quality data from raw smartphone sensors and smartphone usage.

Term	Categories	Description / Explanation	Example
Crowdsensing	Data collection	Data collection technique where information is extracted from mobile devices such as smartphones, tablet computers, or wearables	Collecting data from mobile use on social networks, search engines, mobile operators, online games, and e-commerce sites
Digital dust	Data	Data we share when using digital devices accessing online services, actively or passively. Used as a synonym for digital traces	Data from social networks, search engines, mobile operators, online games, and e-commerce sites
Digital footprint	Data	Sum of all Digital dust, Digital traces, and/or Small data	All data from social networks, search engines, mobile operators, online games, and e-commerce sites
Digital phenotype	Data, Metadata	A human trait described from a trail of health-related data left behind through (user) interaction with technology	Data from social networks, search engines, mobile operators, online games, and e-commerce sites
Digital traces	Data	Data we share when using digital devices accessing online services, actively or passively.	Data from social networks, search engines, mobile operators, online games, and e-commerce sites
Small data	Data	Leave behind a ‘trail of breadcrumbs’ with our digital service providers	Data from social networks, search engines, mobile operators, online games, and e-commerce sites
The Internet of Behaviour (IoB)	Data, Psychology	Change in human behaviours based on collected and used digital dust	Recommending new user experiences, product suggestions, and company services based on the collected digital dust

Table 3. Terms originating from a human-digital context

Digital footprint

A digital footprint is the sum of all the data that we leave behind with or without our consent when we use digital services [21]. This has historically also been referred to as a digital shadow, but given Kritzinger’s [9] definition of a digital shadow, we will not use this definition to mean the same as a digital footprint. Figure 4 illustrates adding up all small data (or digital traces) for a person.

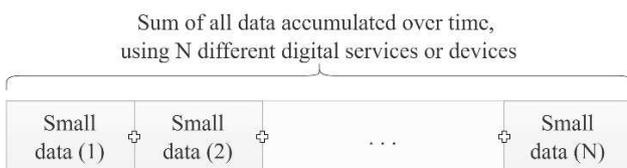


Figure 4. Digital footprint visualised

The Internet of Behaviour

The Internet of Behaviour (IoB) is about collecting and using digital dust from a variety of sources, to change behaviours using feedback loops [22-23]. User data is analysed with regards to behavioural psychology, recommending new user experiences, product suggestions, and company services based on the collected digital dust.

Behavlets

Behavlets are used in gaming (also referred to as videogaming) to extrapolate features from actions or patterns in gameplay which expose player behaviour [24]. Behavlets may be used to improve application interaction

and predict behaviour, approaching research areas such as psychology and temperament theory.

Crowdsensing

Crowdsensing, sometimes called mobile crowdsensing, is a data collection technique where a group of individuals with mobile devices such as smartphones, tablet computers, or wearables, collectively share and extract information with the intention to measure, map, analyse, estimate, or predict processes of common interest. This comes mainly in two flavours, participatory and opportunistic crowdsensing. Participatory crowdsensing is when users voluntarily participate in contributing information, opportunistic crowdsensing is when data is sensed, collected, and shared automatically without user intervention, in some cases without the user's knowledge [25-26].

The Internet of Medical Things

Internet of Things (IoT) is the technology that enables devices with communication capabilities to share data with other devices and systems over the internet [27].

The Internet of Medical Things (IoMT) is a subset of IoT for medical and health-related purposes, data collection and analysis for research, and monitoring [28]. A IoMT device can be almost anything, from personal devices like specialised implants, pacemakers, wristbands, or hearing aids, to "smart beds" or sensors within living spaces or kitchen equipment.

5 DISCUSSION

When used in different contexts, these terms may differ because the particular term synonym fits a particular usage scenario. Problems arise when the exact same term is used as a description of different phenomena. This creates communication difficulties, especially when used across different disciplines or professions, and could hold back the progress of the research field.

There might be several reasons for a term having different meanings. There might be a development over time, where a term definition has been changed due to usage in new areas or introducing new technology. Or there has been a lack of international consensus meetings to operationalise common definitions.

What is noteworthy is that there are different expressions that are applied to the same context. An example of this is the terms *digital dust*, *digital phenotype*, *digital traces*, or *small data*, which all describe the trail of data left behind when using digital services or devices. These all stem from human activity where digital technologies with data storage are used.

The definition of a digital thread and a digital footprint may on the surface look similar. The difference is that a digital thread logs all changes over time, while a digital footprint is a snapshot of all the existing data, not factoring in updates and history.

Digital twin terms, from manufacturing to healthcare

One question to ask is if terms in manufacturing belong in a human or a healthcare context. Creating a human digital twin as previously defined in manufacturing does not seem fully attainable, with a bi-directional dataflow between physical entity (the human) and the digital model. This would mean “updating the human” based on data in the digital model, although this might be partly realizable through changes in medication (e.g., for advanced insulin pumps in diabetes self-management) or by updating physical implants digitally, but not in all respects. The human body is still not fully physiologically understood, so creating a perfect digital copy with bi-directional updates seem unattainable.

The one-directional flow of data from the physical entity (human) to the digital model seems more plausible. In a human context, the *digital shadow* can be viewed as the digital equivalent of living a life, monitoring all processes

in the body as life happens, with the Human Digital Thread as a history or log of human data/events/updates.

The *digital thread* could be viewed as the log or history of all dataflows to update the digital shadow or digital twin. In a human context this can be defined as all the small data that is generated by human activity in different contexts, using phones (smart or not), general mobile app usage, computer usage, or online services. This is illustrated in Figure 5. The digital thread consists of multiple data events, here referred to as small data instances (slices), over a period of time. This describes a continuous history of the digital shadow or digital twin. The digital shadow or twin is defined by the latest iteration or data update in the lifetime of the entity. This is always the “now”, the current time, given that there are continuous updates to the digital representation. This would be the case for human digital twins.

One way of imagining a digital twin of a person, is to avoid creating an exact digital copy of the individual. Accepting that there are areas we cannot – yet – recreate digitally, opens the possibility for creating a semi-automatic feedback loop where monitoring and registering data for an individual may give direct or indirect feedback to the individual through software or technology. This is in many ways what we have today, though not as a complete system. Wearing smartwatches or using smart scales sends health-related data to servers, and feedback are given through e.g., mobile applications. These kind of data sources are narrow in scope, in that they register parameters like activity and weight, but does not consider all sorts of other sources of information like weather conditions, road dust, mental state, illnesses, season variations, and similar. Creating this wider definition of a human digital twin could in the end be valuable for public health, health care providers, policy makers, and others, as well the person him/herself. This type of system could also be valuable for population studies similar to The Tromsø Study [29].

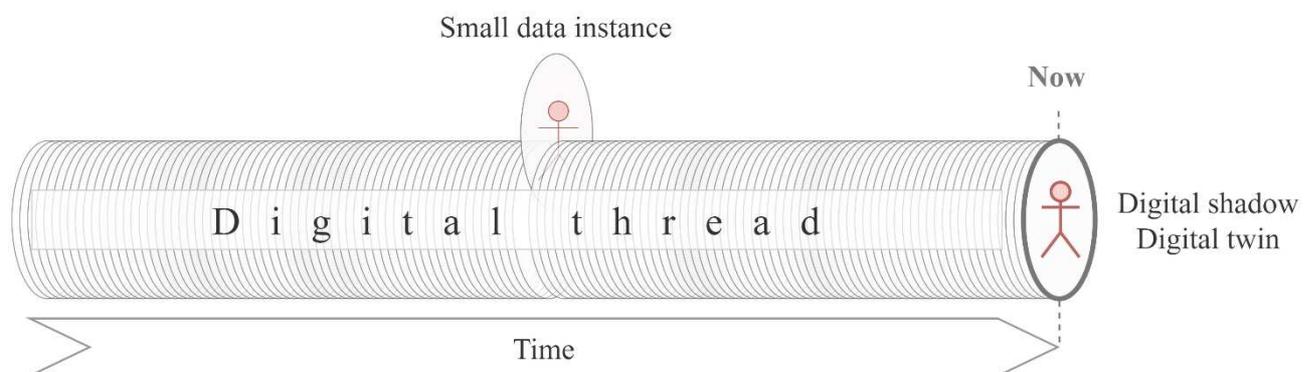


Figure 5. Digital thread, small data, and digital shadow (or digital twin) illustrated

6 SUMMARY

We have examined digital twin and related terms and concepts and how they fit in the healthcare area. A human digital twin is currently not fully realisable, but there are untapped possibilities for creating a more complete human digital twin today, by joining different types of data from a heterogenous set of services and sources. If we can exploit these possibilities, we can approach an approximation of a digital twin for use in healthcare.

7 REFERENCES

- [1] M. Grieves, 'Digital twin: manufacturing excellence through virtual factory replication', *White paper*, vol. 1, pp. 1–7, 2014.
- [2] R. Saracco, 'Digital Twins: Bridging Physical Space and Cyberspace', *Computer*, vol. 52, no. 12, pp. 58–64, Dec. 2019, doi: 10.1109/mc.2019.2942803.
- [3] Lindsey Andrews, 'The Term Digital Twin is a Buzzword', *SensrTrx | Manufacturing Analytics*, Feb. 18, 2020. <https://www.sensrtrx.com/digital-twin-buzzword/> (accessed Oct. 03, 2021).
- [4] "digital twin*" - Google Search'. https://www.google.com/search?q=%22digital+twin*%22 (accessed Feb. 24, 2022).
- [5] C. Semeraro, M. Lezoche, H. Panetto, and M. Dassisti, 'Digital twin paradigm: A systematic literature review', *Computers in Industry*, vol. 130, p. 103469, Sep. 2021, doi: 10.1016/j.compind.2021.103469.
- [6] S. M. Schwartz, K. Wildenhaus, A. Bucher, and B. Byrd, 'Digital Twins and the Emerging Science of Self: Implications for Digital Health Experience Design and "Small" Data', *Frontiers in Computer Science*, vol. 2, 2020, Accessed: May 28, 2022. [Online]. Available: <https://www.frontiersin.org/article/10.3389/fcomp.2020.00031>
- [7] D. Jones, C. Snider, A. Nassehi, J. Yon, and B. Hicks, 'Characterising the Digital Twin: A systematic literature review', *CIRP Journal of Manufacturing Science and Technology*, vol. 29, pp. 36–52, May 2020, doi: 10.1016/j.cirpj.2020.02.002.
- [8] M. S. Househ, B. Aldosari, A. Alanazi, A. W. Kushniruk, and E. M. Borycki, 'Big Data, Big Problems: A Healthcare Perspective', *Stud Health Technol Inform*, vol. 238, pp. 36–39, 2017.
- [9] W. Kritzinger, M. Karner, G. Traar, J. Henjes, and W. Sihn, 'Digital Twin in manufacturing: A categorical literature review and classification', *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 1016–1022, Jan. 2018, doi: 10.1016/j.ifacol.2018.08.474.
- [10] M. M. Rathore, S. A. Shah, D. Shukla, E. Bentafat, and S. Bakiras, 'The Role of AI, Machine Learning, and Big Data in Digital Twinning: A Systematic Literature Review, Challenges, and Opportunities', *IEEE Access*, vol. 9, pp. 32030–32052, 2021, doi: 10.1109/ACCESS.2021.3060863.
- [11] robert.lipman@nist.gov, 'Enabling the Digital Thread for Smart Manufacturing', *NIST*, Dec. 04, 2014. <https://www.nist.gov/el/systems-integration-division-73400/enabling-digital-thread-smart-manufacturing> (accessed Mar. 07, 2022).
- [12] J. Howison, A. Wiggins, and K. Crowston, 'Validity Issues in the Use of Social Network Analysis with Digital Trace Data', *Journal of the Association for Information Systems*, vol. 12, no. 12, Dec. 2011, doi: 10.17705/1jais.00282.
- [13] 'What Is "Digital Dust" and Should We Worry About Ours?' <https://www.linkedin.com/pulse/what-digital-dust-should-we-worry-ours-ema-linaker> (accessed Mar. 07, 2022).
- [14] N. Wright, 'Death and the Internet: The implications of the digital afterlife', *First Monday*, May 2014, doi: 10.5210/fm.v19i6.4998.
- [15] E. Casey, 'Digital dust: Evidence in every nook and cranny', *Digital Investigation*, vol. 6, no. 3, pp. 93–94, May 2010, doi: 10.1016/j.diin.2010.02.002.
- [16] C. Bernardi, 'Digital Dust and Visual Narratives of Femicidios', *Visual Culture & Gender*, vol. 13, pp. 6–16, Sep. 2018.
- [17] 'Grey Literature: Digital scholarship or digital dust', *ABC Radio National*, Feb. 25, 2013. <https://www.abc.net.au/radionational/programs/bigideas/grey-literature/4529562> (accessed Jan. 12, 2022).
- [18] D. Estrin, 'Small data, where n = me', *Commun. ACM*, vol. 57, no. 4, pp. 32–34, Apr. 2014, doi: 10.1145/2580944.
- [19] S. H. Jain, B. W. Powers, J. B. Hawkins, and J. S. Brownstein, 'The digital phenotype', *Nat Biotechnol*, vol. 33, no. 5, Art. no. 5, May 2015, doi: 10.1038/nbt.3223.
- [20] J. Torous, M. V. Kiang, J. Lorme, and J.-P. Onnela, 'New Tools for New Research in Psychiatry: A Scalable and Customizable Platform to Empower Data Driven Smartphone Research', *JMIR Mental Health*, vol. 3, no. 2, p. e5165, May 2016, doi: 10.2196/mental.5165.
- [21] M. Madden, S. Fox, A. Smith, and J. Vitak, 'Digital Footprints', *Pew Research Center: Internet, Science & Tech*, Dec. 16, 2007. <https://www.pewresearch.org/internet/2007/12/16/digital-footprints/> (accessed Mar. 08, 2022).
- [22] 'Gartner Top Strategic Technology Trends for 2021', *Gartner*. <https://www.gartner.com/smarterwithgartner/gartner-top-strategic-technology-trends-for-2021> (accessed Mar. 07, 2022).
- [23] 'What is the Internet of Behavior and Why is it Important for Business?' <https://gbksoft.com/blog/internet-of-behaviors/> (accessed Mar. 07, 2022).
- [24] B. Cowley and D. Charles, 'Behavlets: a method for practical player modelling using psychology-based player traits and domain specific features', *User Model User-Adap Inter*, vol. 26, no. 2, pp. 257–306, Jun. 2016, doi: 10.1007/s11257-016-9170-1.
- [25] B. Guo *et al.*, 'Mobile Crowd Sensing and Computing: The Review of an Emerging Human-Powered Sensing Paradigm', *ACM Comput. Surv.*,

- vol. 48, no. 1, p. 7:1-7:31, Aug. 2015, doi: 10.1145/2794400.
- [26] R. K. Ganti, F. Ye, and H. Lei, 'Mobile crowdsensing: current state and future challenges', *IEEE Communications Magazine*, vol. 49, no. 11, pp. 32–39, Nov. 2011, doi: 10.1109/MCOM.2011.6069707.
- [27] 'Internet of Things Global Standards Initiative'. <https://www.itu.int/en/ITU-T/gsi/iot/Pages/default.aspx> (accessed Jan. 11, 2021).
- [28] A. Gatouillat, Y. Badr, B. Massot, and E. Sejdić, 'Internet of Medical Things: A Review of Recent Contributions Dealing With Cyber-Physical Systems in Medicine', *IEEE Internet of Things Journal*, vol. 5, no. 5, pp. 3810–3822, Oct. 2018, doi: 10.1109/JIOT.2018.2849014.
- [29] L. A. Hopstock, S. Grimsgaard, H. Johansen, K. Kanstad, T. Wilsgaard, and A. E. Eggen, 'The seventh survey of the Tromsø Study (Tromsø7) 2015–2016: study design, data collection, attendance, and prevalence of risk factors and disease in a multipurpose population-based health survey', *Scand J Public Health*, p. 14034948221092294, May 2022, doi: 10.1177/14034948221092294.

8 ACKNOWLEDGEMENTS

The study was funded by UiT the Arctic University of Norway.