

# Ethical Gathering of Exercise Metrics from Elderly: Case Jumppatikku

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**Abstract.** Health gaming for elderly, alongside with other game types, have become an emerging trend amongst video game industry. As all emerging technologies, it brings some ethical questions which – as usual – are better solved before implementation, for the values these choices reflect to be embedded into the design. In this paper we introduce a case example of the elderly activation system Jumppatikku (‘Exercise stick’) and analyse the main ethical questions of the specific case example, as well as take into consideration other similar systems from the viewpoint of ethical design and responsible research and innovation.

**Keywords:** Responsible research and innovation · Elderly · eHealth · Mobile · Ethical design

## 1 Introduction

In this paper we introduce an ethical dilemma on elderly healthcare. During the 2000s and 2010s many different digital aids for activating and caring of elderly has been developed. These activation aids and methods rise several challenges which may, in the worst case endanger the privacy and security of these senior citizens.

The dilemmas are analysed through a variety of ethical theories. Both consequences [1] and intentions (see e.g. [2]) of any system we build should be considered when thinking of whether the system is morally good, or at least acceptable (See e.g. [3]). In this paper the case of the *Jumppatikku* (“Exercise stick”) is analysed from both of these perspectives. It is clear that the intention of the group developing the device and the related systems is good – the aim of the system is, after all, the wellbeing of the elderly for whom it is being designed – on top of which it is hoped to take into account and solve any various unintended consequences on a satisfactory level. Since considerations typically raised in IT and ethics field cover such as professional virtue (on virtue ethics, see e.g. [4]), ethical discourse [5], and considerations for those in the weakest positions [6], this paper is focused on (unintended) consequences of actions. The selection is intended to act as an opening of discussion on the topic, and consider a field not already

covered by the design of the project activities. In the Jumppatikku project those who are in the weakest position are taken into account in designing a device and a system that will be available to all elderly irrespective of their financial or social status in Finland, this paper itself is part of the ethical discourse (albeit not purely in the sense Habermas intended), and we have no reason to suspect the professional integrity of the designers of the system.

In the 2<sup>nd</sup> and the 3<sup>rd</sup> sections the field of elderly health gaming, the Jumppatikku project and related, possible metrics that can be derived with these kinds of systems are introduced. This research is a theoretical ethical study from the Jumppatikku research project to ensure the ethical validity of the Jumppatikku exercise system. Thus in 4<sup>th</sup> section the ethical dilemmas are introduced and discussed.

## 2 Background

### 2.1 Games for Elderly

Primary interests for the usage of games with elderly are related to the training of memory, cognitive skills, and physical training. With the cognitive skills and memory the main aim is the prevention and slowing down the decline of memory. Muscle and balance training games are targeting fall prevention as falling related injuries (e.g. hip and wrist fractures) are one of the leading causes affecting the quality of life of elderly population. Some of the commercial off the shelf (COTS) training games are created and marketed for the elderly, but mostly they are created for wider audience.

The general (non-sedentary) games aiming at increased activity levels (e.g. dancing games based on body movements) have several differing limitations with elderly players. Such games use different techniques on detecting player's body movements, and depending on the method, players with physical limitations might have problems on using them. In general movement based games the target audience is relatively younger and the gameplay requires movements and/or positions that are not possible for some or most of the elderly players. Some of these games use physical devices (e.g. WiiMote) that contain buttons or require constant force for holding the device in hand for prolonged time, causing discomfort for elderly players.

In the more specialized use cases, meaning research and therapy sessions, the main reason for the usage of such games are the same as with the COTS games. Games for therapy sessions are specially made for therapies and even targeting the elderly only, but in many cases the games used are regular COTS games. The same principle applies to the research settings. As an example of COTS games used, the Super Mario game has been used to study the effects of gaming on the brain structure of the elderly subjects [7] with promising preliminary results. As a custom counterpart for this game similar trend in results has been found with the Neuroracer [8].

### 2.2 Advertising and Data Mining

Advertising and data mining has been an upward trend in games for at least the past decade. For example, in-game advertising has grown from generating around \$34

million in 2004 to an estimated \$7 billion by 2016 [9, 10]. The rise of social online games can be identified as one of the major explanations for the observation. Especially Free-to-Play (F2P) games rely heavily on income from advertisers. Data mining in games, particularly that of player behaviour has been an important source of information especially in games that generally have long persisted online worlds. Game developers of these games have a constant need to add new content to keep the players engaged and for that they need data on preferred solutions and settings of the game, directly from the users. Free-to-Play games and Massive Multiplayer Online Games (MMOGs) are the most common games for data mining, and as such those games have been pushing data mining in games to new heights [11].

What is game data mining exactly? Game data mining can be seen as an insight, formed by utilising the collected game metrics and game telemetry. Game telemetry is the raw data collected from a game, such as player location at a given time or play time. Game metrics, on the other hand, are data formed from game telemetry using simple aggregation. Average play time calculated from raw play times could be a game metric, or hotspots of players could be another. Game data mining in this example, could be seen as the process of getting insight on why the spot is a hotspot and what does it mean in terms of gameplay [12].

### 2.3 Capitalizing on the Game Data

The capitalization of the mined data varies depending on the game needs, but generally the focus is on improving gameplay and monetization. Gameplay can be improved in a number of ways. For instance, IO Interactive used heat maps composed of player character deaths in Kane and Lynch 2: Dog Days, a game developed by them, to get insight on the workings of the gameplay. In this particular case, the data revealed that there was a surprisingly high amount of team kills at a certain map location, but that otherwise the gameplay was as designed [13]. A common way to gain from the game data in the form of monetization is to inspect what kind of downloadable content (DLC) players, and especially players spending the most, are interested in, and focusing on creating content for them.

## 3 Metrics

### 3.1 Existing and Theoretical Metrics

The abundance of possible game metrics has led to a number of categorizations for them. Categorization by Mellon [14] divides game metrics to player metrics (also known as user metrics), performance metrics and process metrics (sometimes known as pipeline metrics). Process metrics consist of metrics related to the development process and as such is only of interest for a limited set of people. Performance metrics are metrics on the game performance with frames per second (FPS) being the usual example of a performance metric. This is also a metric that generally only interests certain people, such as developers working on optimizing the game. The third and the most relevant category in considerations of capitalising on the game data, is the category of player

metrics. Player metrics consist of all the metrics related to what the player does, and therefore can give an insight of choices and preferences of the players. It is the category that most of the research and discussion related to game analytics concern. Player metrics can again be divided to either generic, genre specific and game specific categories, or as suggested in Drachen et al. [15] to customer, community and gameplay metrics. Customer metrics cover metrics related to the player as a customer and are mainly of interest for sales and marketing teams, such as customer retention rates. Community metrics tell about the players' involvement in the game community. Such metrics are usually collected from for example game forums explaining the activity levels of the entire community and are mainly for community managers. Gameplay metrics are related to what the player actually does and how he or she behaves in the game and pretty much consist of rest of the metrics. They essentially answer the questions of what the player did, where, at what time and which player(s) were involved. The last sub-categories are of gameplay metrics, which is yet divided to interface, in-game and system metrics. System metrics are collected from actions initiated by the game engine in response to player actions, such as unlocking an achievement. Interface metrics consist of the players' actions in the game menus and other possible interfaces in the game. In-game metrics are the metrics of what the player does in-game. Everything that does not fit the first two sub-categories fall under the in-game metrics [15].

The concrete metrics collected in games depend on the game itself, on its genre and of course, on which metrics the developers are interested of. Some core metrics, such as length of the gameplay session, can be collected from most if not all games regardless of the game type, but the majority of metrics only make sense in specific games. Most of the games for the elderly promote health in some way, be it physical or mental health, and as such they tend to be either fitness or puzzle games. In a fitness game the important metrics collected could represent such choices as which exercises were chosen, which were performed, how well and often were they performed as well as how many calories was burned in each session and in total. A puzzle game might collect metrics on which puzzles the player has given a go on, which of the puzzles he or she passed and how often, how he or she passed them (order of moves or choices), how long did it take to either complete a specific puzzle or for example, how long did the player try to solve it. These are noticeably more intimate metrics than what can be collected from other games in the sense that they are directly related to the players' physical and mental abilities, even more so when the game especially targets the elderly. For instance the pattern of how the player might try to keep solving a puzzle wrongly might reveal a decline in some cognitive skills or the inability to properly perform a certain exercise could give a strong indication of a physical disability [15, 16].

The possibilities of physically tracking the player with gaming devices, be it a mobile phone or a game console, are becoming more and more plentiful as more sensors are added and their accuracy enhanced. Naturally this leads to game developers being able to create better experiences for the players, but it also means more data and more accurate data for those collecting the metrics. As mentioned above, this data is potentially rather valuable, at least if compared to such other examples of metrics, like how many frags a player gets in a FPS game. The TI SensorTag, which the Jumppatikka ("exercise stick") uses, has six sensors: pressure, humidity, temperature (IR), accelerometer, gyroscope

and a magnetometer. The new (2015) version of SensorTag also has a light sensor, making the total amount of different sensors to rise to seven [17]. At the time of writing, Jumpatikka has six moves which it can track and detect: squats, leg lifts, leg swings, leg rotations, hand swings and body twists. Body twists and foot rotations are both tracked using the accelerometer and gyroscope, but the rest of the moves only make use of the accelerometer. In essence just the two of these very basic sensors are enough to determine a variety of moves and possibly get hints of the players' physical condition. Add in a few external sensors, such as a heart rate sensor or a blood pressure sensor, plus some creative thinking and there is a huge amount of information that one could deduce about the player.

### 3.2 Examining Metrics

Following the previous categorizations we can discuss genre specific metrics that relate to all health games that use imaging or movement sensors. In the case of interface metrics we collect data about subjects' actions with the application itself. This data can be used to measure how fast or how well they can use the interface. If data is collected for longer periods of time, the change in this data can reveal changes in physiological and cognitive performance. In the case of health games aimed for the cognitive effect, the in-game player performance data can directly concern the decline or improvement (or steadiness) of subjects' memory, visual attention or other cognitive skills (see e.g. [18]).

The body movement data and imaging sensors produce vast quantities of data which can be mined with specific algorithms. Modern imaging sensors and their 3D data can be used to measure heart rate from micro-fluctuations in surface veins on the face of the subjects of the study [19]. Facial micro-movements and gaze tracking can be used to reveal signs of depression [20]. Combining different methods, the gaze tracking can potentially be used to track what kind of visual stimuli interests the subject based on their voluntary or involuntary micro-expressions [21].

In the case of Jumpatikka, where the player data is collected from sensors located on the subjects hand or body, we have a variety of possibilities for data mining [22, 23]. With the sensor package and data collecting application we can receive data, including GPS-coordinates, accelerometer data, physical performance from the game's interface and in-game metrics related to the usage of the app and scores from the tasks itself. (See Fig. 1.)

From this data set, the obvious findings are current location and hotspots where the subject tends to be during normal days. By combining these with other data sources we can deduct when and where the subject might be during certain days and times [24]. Further, finer grained accelerometer and gyroscopic data can be used to track the limb movements of the subject. (See Fig. 2.) With data mining algorithms and learning neural networks, we can potentially monitor the development of diseases like Alzheimer and Parkinson's disease, or measure the gait of the user which can be used to predict the subjects' tendency to fall which can be used as a signal to guide them to either do certain exercises or seek related help (e.g. [25–27]).



**Fig. 1.** Using Jumppatikku.



**Fig. 2.** Exercising by standing up and sitting down with Jumppatikku.

Accurate and ubiquitous sensors can also be used to track fine-grained hand movements. This, combined with advanced algorithms has led to a situation where data mining of movement data can reveal personal information about the subjects. This includes their physical actions like hobbies, potential physically manifesting illnesses and even PIN-numbers they might punch in daily [28].

## 4 Gathered Information and Ethics

As mentioned before, the system contains a huge amount of information. That information can, in wrong hands make the subject of the information vulnerable. There are several ways to protect the subject from these vulnerabilities, e.g. by limiting the access to the information, by securing it or by not collecting it in the first place. When the information is not collected one can be sure it cannot be misused. The difficulty with this method is to understand what information is relevant and what is not.

Limiting access brings forth some questions, foremost who should be told and what? From the raw data several things, such as timestamps or the diagnosis for Parkinsons' disease can be derived when the data is pre-analysed and transformed into information the medical personnel can interpret easily without the need to deliver the private information to them. This information is none-the-less sensitive information.

Moreover, the data, such as timestamps and movements, still stay in the servers. Hence, if the main system can be hacked, and if it logs location information (or something that can be interpreted as such) the information can be used to access elderly persons' homes for example for burglary. Thus, it must be taken care of that location info is not saved and that the system might give an impression for a casual hacker that it would be used in multiple locations (whether that is true or not).

This of course holds true for other parties as well – access to the system should be only on need-to-know, and of course, on *informed* consent basis.

Ownership or control of the data: to avoid undue paternalism, the default control of the data must be held by the user (see e.g. [29, 30]). If the users do not want to share their data with any particular parties – even if those parties are health care professionals – they must be able to choose so unless there are special reasons such as far advanced dementia or public health hazard.

Data control video recording is possible with X-Box and similar devices. If these kinds of devices are used, there is a need to be very careful indeed that the video material so collected does not fall into the hands of others than those who need the data for diagnostic purposes.

It must be noted that even though the system can alert the medical personnel if it recognises a risk of e.g. Parkinson's disease the system is not a doctor, and thus there is no doctor-made diagnosis and the alert should only be a guideline for the patient to see a doctor, and for the doctor to see a patient. Systems like this are not decision making systems, but only alert systems. There are two challenges with this: first we need to be aware of the patient's right to privacy and information security (handled below) and secondly, patient's right to a correct diagnosis. Even if the system could deliver 95 % accurate prognosis it still – according to the medical traditions and legislation – is not a diagnosis (nor should it be). That information, therefore, is still a prediction and thus should be handled as such because false positives could affect the patients' behaviour. This can cause unnecessary and unwanted fear and pain for the patient when he or she is both afraid of the sickness and still waiting – in many cases for days, weeks or even months – for guidelines and diagnosis from his or her MD. Thus, there is an ethical dilemma: should the information about e.g. Parkinson's disease be visible to the user or just for the treating medical personnel? We need to note that this is not data from the



system but a mere speculation by the system and it is not under the direct control of the user. The medical professionals can then use the data to deduct a diagnosis of the disease (or lack thereof). The patient typically does not have the necessary skills to do this, and thus should not be put in a position to try and worry about it.

While it is obvious that information security must be high in the server end, it must also be protected in the user's device. While the mobile device contains various kinds of information on the activity of the user, it should never reveal daily activities (at least time stamp and location) because the person using the device might not be the elderly person him- or herself. If the privacy of the user is leaked by the system for example to the person's relatives, it can harm the patient in situations where the relatives are not that trustworthy.

In essence the privacy of the user is in straight contradiction with the patient's right to see his or her own (medical) information when the user of the mobile device is someone else than the patient themselves. Therefore that person's information should be locked so that the users can leave their phone still in *swipe to open* mode (which tends to be a familiar password with elderly persons' mobile devices), or let their relatives call or send a message without fear of them accessing their medical information.

The device should not save the data to the device itself (due to security concerns), but rather the (useful and required) data should be stored on a server to which the user has access via a secured connection not included in the device itself. None-the-less, any speculations by the system always need to go through a medical professional – and the system should have an alert whenever it is deducting a pattern matching a disease – before the patient has access to this deduced information. This is not against the right of the patient to control their information (see e.g. [29, 30]), as the deduced speculation is not yet known about the patient but only *speculation* about the patient's condition, and might prove out to be wrong.

Responsible Research and Innovation [31] can be used as a way to ensure ethics in design (see also [32]). If the designers do not possess the required character, although they should and this should be the aim through professional development, a sub-project in a R&D project that covers ethical and social aspects can be built in the project instead. A part of the sub-project should be research governance as a way to also remain sensitive to broader concerns such as social acceptance. The main point however is that both the societal actors and innovators should be helped to become mutually responsive to ethical issues in any design project. Reflexivity through ethics is paramount to enable this ([31], but see also [33, 34]).

## 5 Conclusions

The overall intent for the Jumppatikku is obviously good and the desired consequences seem valid. The idea of creating a good life and better health for the elderly seems indeed to be virtuous. Yet there are a few problems with the whole idea of data gathering with sensors that must be kept in mind. In this paper we have looked at these problems, and offered solutions through the use of ethical design methods, taking into account the various different possibilities that could go wrong and how to actually solve them in this



context. Of course, this study is only a case study of the Jumppatikku, so any lessons learned should be understood in this context. However, most if not all of them can be used in similar situations as-is or at least with very little modification. Of course, in any project a reflection of methods used in other projects is always in order.

We hope, that we have shown that even quite simple looking and clearly good intentioned projects need ethical consideration so as to not misuse the collected data or the device itself; to help projects such as Jumppatikku achieve maximum benefits and as few drawbacks as possible.

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