

Modular Playware and Personal Health Technology

Henrik Hautop Lund

Center for Playware, Technical University of Denmark, Building 326, 2800 Kgs. Lyngby, Denmark

E-mail: hhl@playware.dtu.dk

www.playware.elektro.dtu.dk

Abstract

In this paper, we describe the development of personal health technology such as wearable systems monitoring health conditions. It has been advocated that such personal health technology through monitoring health status may motivate people to perform health related actions and life-style changes. Here we describe a methodology on how these personal health technologies may rather be used as a tool for designing and adapting game activities, which motivate people to perform the desired actions. Especially, we exemplify this methodology with the use of FitBit monitoring of steps and heart rate to the design of appropriate, physically demanding games for the modular interactive tiles, Moto Tiles, which are used by older adults for prevention and rehabilitation. Thereby, the motivation to perform the actions arrives from the fun play on the Moto Tiles, whereas the personal health technology is used as a tool to monitor the effect and guide the game development.

Keywords: Playful technology, Playware, Personal Health Technology, FitBit, Adaptive Games.

1. Introduction

Personal health technology such as different wearable systems monitoring health conditions have been developed over the last decade and finds its way to the general public. These personal health technology devices are often described as a means to engage and motivate the public to perform health related actions, and e.g. change behavior to become healthier. A typical example is that wearing a step counter is believed to engage and motivate people to perform more steps (walk more, run more, bike more, etc.) due to goal setting (e.g. 10,000 steps per day) and insight into their own performance (how many steps did I take today?). As such, the personal health technology is viewed as a *persuasive technology* [1]. Persuasive technology is technology designed to change people's beliefs and behaviors, e.g. creating certain health habits amongst the users of the technology product.

With this view of personal health technology as a persuasive technology, researchers and practitioners have investigated *nudging* through the new opportunities arising with the technology. It is well-known that information, priming, peer pressure, etc. may guide people to certain behavioral actions (e.g. choosing a certain behavior) – this has nowadays been termed nudging. Nudging with personal health technology includes the simple nudge that an arm wrist wearable acts as a physical reminder to be active, and the interface on the physical device or the app acts as a positive or negative reinforcement by presenting e.g. statistics, target amount, and time since last action.

There are numerous health nudging apps and devices for hydrating, moving, sleeping, etc. It appears that the main idea of nudging in these kind of personal health persuasive technologies is based on presenting a numerical indicator, a graph and a numerical goal, which translates to nudging/persuading the user by providing

© The 2018 International Conference on Artificial Life and Robotics (ICAROB 2018), Feb. 2-4, B-Con Plaza, Beppu, Japan

the user with an insight into the personal health status. Such an insight is believed to be a strong enough motivation for people to perform more of the desired healthy behavior.

In this context, the connotation of nudging is that such an insight into personal health measurements is such a strong motivation that people will perform more of the desired healthy behavior. Accordingly, the numerical insight into one's own personal health should act as a strong *extrinsic motivation*.

However, it is questionable if everybody will respond well to such a nudging based on numerical insight into one's own personal health acting as a strong extrinsic motivation. Will everybody act equally well to such information? For instance, it is known from message tailoring that adapting persuasive messages to recipients' characteristics is more effective than providing the same message to all recipients, since recipients with different characteristics will respond more or less to the same message. For instance, Hirsch et al. [2] demonstrated effective message tailoring using a comprehensive model of recipients' personality traits. "Respondents judged an advertisement emphasizing a particular motivational concern as more effective when that concern was congruent with their own personality characteristics. Message-person congruence effects were thus observed by manipulating the framing of an appeal to target a broad variety of motives, including desires for excitement and social rewards (extraversion), connection with family and community (agreeableness), efficiency and goal pursuit (conscientiousness), safety and security (neuroticism), and creativity and intellectual stimulation (openness/intellect)." [2]. These are termed the Big Five personality dimensions:

- Openness to experience: (inventive/curious vs. consistent/cautious).
- Conscientiousness: (efficient/organized vs. easy-going/careless).
- Extraversion: (outgoing/energetic vs. solitary/reserved).
- Agreeableness: (friendly/compassionate vs. challenging/detached).
- Neuroticism: (sensitive/nervous vs. secure/confident).

Indeed, it is important to distinguish between *extrinsic* and *intrinsic* motivation [3], as the Big Five personality model may predict motivation in e.g. education, sports, and exercise, where the Big Five traits are associated with different levels of self-determined motivation. Hence, people may be motivated to different degrees and not all are given to respond positively to extrinsic motivation such as the nudging suggested by the personal health technologies. For instance, Hart et al. [4] found that "Conscientiousness, openness, and extraversion were positively associated with intrinsic achievement motivation, whereas extraversion, conscientiousness, and neuroticism were positively related to extrinsic achievement motivation. Agreeableness was also found to be negatively associated with extrinsic achievement motivation. Conscientiousness was anomalous in that it was positively related to both intrinsic and extrinsic motivation."

To investigate the effect of intrinsic motivation in personal health technology, we suggest to put focus on play. Play is often defined as a free and voluntary activity that you do with no other purpose than play itself and for the enjoyment that it brings [5]. There is no product or outcome as such of play, but people play for their own enjoyment and fulfillment, i.e. there seems to be an intrinsic motivation to play, when people are in a play dynamics. Hence, it becomes interesting to understand how people enter into such a play dynamics, in which they fully engage in play and seem to forget about time and place. It has been suggested that there exists play forces, which drive people into a play dynamics, and that playware can act as such a play force [6]. The hardware and software augmentation of objects to become playware [7, 8] may for instance draw people into moving, touching, turning, etc. due to emission of sound, light, odor, etc. and immediate explicit feedback from the playware drive people into further actions, acting as a play force pushing people into a play dynamics of continuous actions and feedback.

Even if there is no product or outcome of such play based on the intrinsic motivation for own enjoyment, there may be *collateral effects of play* [9]. For instance, the collateral effects of play can be motor skill enhancement, cognitive and physical rehabilitation, etc. These

collateral effects of play, e.g. on the health, can be significant and important [10].

Therefore, in the present work, we put focus on the creation of playful experiences and intrinsic motivation. So instead of viewing the personal health technology as a motivational tool with the health status as the primary effect, our methodology involves the personal health technology as a tool for designing and adapting game activities, which are the ones to intrinsically motivate people and with which the health status is a collateral effect.

2. Method

We exemplify the methodology with the use of FitBit monitoring of steps and heart rate to the design of appropriate, physically demanding games for the modular interactive tiles, Moto Tiles [11], which are used by older adults for prevention and rehabilitation. Thereby, the motivation to perform the actions arrives from the fun play on the Moto Tiles, whereas the personal health technology is used as a tool to monitor the effect and guide the game development.

There is an important distinction to be made between the general *long-term effect* and the *short-term effect*. It is possible to measure both the short-term effect and the long-term effect, and it is clearly interesting to obtain knowledge of the potential relationship between the short-term effect and the long-term effect.

The general effect of an intervention can typically be measured in pretest and posttest in a randomized controlled trial (RCT) with comparison between the intervention group and the control group. In our case here, we view this as a long-term effect compared to the short-term effect (or we can even call this the run-time effect), which is typically provided with the personal health technology such as the FitBit. The short-term effect or run-time effect may be measured as physical activity level (e.g. steps, heart-rate, etc.) or mental activity level (e.g. blood flow in prefrontal cortex to indicate concentration).

Here we propose that the short-term effect measurements can be used for designing for increasing the long-term effect (the collateral effect of play).

This demands that there is a relationship between the short-term (run-time) effect measurement and the long-term effect, and that we can find such relationship(s). This clearly depends on the selection of which short- and long-term health parameters we are looking at, i.e. which physiological states are measured and with which measuring tools at short-term and at long-term. It will be a whole field in itself (e.g. within AI and Big Data) to find this coupling and relationship for the range of measuring tools, measurements and intervention areas. Here, we are therefore limited to provide only a first idea. Nevertheless, to exemplify this approach, in this study, we use a personal health technology, Fitbit, to measure run-time effects and their correlations with scores from playing on the Moto tiles

Fitbit is an activity tracker, which is wireless-enabled wearable technology that measure number of steps walked, heart rate, sleep pattern, and steps climbed. It is worn as a wristband, and connects to a mobile app synched via Bluetooth. In this study, we use the Fitbit to measure heart rate and steps.

Moto tiles are modular interactive tiles used for playful prevention and rehabilitation by allowing users to play different games on the tiles that light up in different colours [11]. The Moto tiles can be put together like puzzle pieces in different patterns, and different games can be selected from a tablet to be played on the Moto tiles. In a game, the user typically will have to move around to hit different tiles according to the game pattern. In the present study, we use three games called Color Race, Final Countdown, and Reach (see videos of the games [12]).

3. Experiments and Results

In the first experiment, we used the Fitbit and Moto tiles data collection to investigate potential relationships between physiological measurements and game score in different games. The hypothesis was that there exist such relationships, and that these may guide future game

design to create games, which may result in collateral health effects of play.

A university student would wear the Fitbit while playing each game in different tiles configurations each 10 times. The first configuration were 2*3 tiles connected together in a rectangle with the games Color Race, Final Countdown and Reach. The second configuration was 2, 2, and 2 tiles put in a triangle with 1.5m in between each of the 2 tiles islands with the games Color Race and Final Countdown. The third configuration was 2, 2, and 2 tiles put in a triangle with 2.5m in between each of the 2 tiles islands, and with the games Color Race and Final Countdown.

Table I shows the Pearson correlation coefficients between the Moto game score of each game and the different activity data collected from the Fitbit (the end heart rate, the maximum heart rate during a game, the rise in heart rate during a game, and the number of steps measured during a game).

Table I. Pearson correlation coefficients between different activity data and game score (α=0.05).

Game	End HR	Max HR	Percentage HR rise	Step
Color race (2*3)	0.5996	0.6030	0.3438	0.9392
Final countdown (2*3)	0.6927	0.6827	0.5268	0.8520
Reach (2*3)	0.8029	0.7908	0.6823	0.8842
Color race (triangle, 1.5m)	0.7522	0.8146	-0.2557	0.9143
Final countdown (triangle, 1.5m)	-0.3909	-0.3021	-0.3836	0.8333
Color race (triangle, 2.5m)	0.6645	0.8093	-0.2770	0.7664
Final countdown (triangle, 2.5m)	0.5793	0.5262	0.5127	0.4868

It can be seen that both the end HR data and max HR data are able to show positive correlation in 6 out of the 7 cases, which is apparently more reliable than percentage change in HR. The average correlation coefficients of the 6 successful cases of end HR and max HR are 0.6819 and 0.7044 respectively, which implies that max HR can be a better indicator of the game intensity. In addition, the result of steps shows fairly strong correlation with Moto game score in all games.

The general indication of this small pilot study is therefore, for these six cases, a higher Moto game score signifies that the user has taken more steps and have reached a higher heart rate. It is therefore indicated, in this case, that the run-time effect is predictable from the Moto game score.

In order to investigate the relationship between the run-time effect and the long-term effect, we conducted another pilot study. In this case, 11 older adults performed Moto tiles training twice a week for 10 weeks in a senior activity center in Lyngby municipality, Denmark, as part of the EU project REACH. The older adults were pre- and posttested with standard tests such as timed-up-and-go, chair-to-stand, 6 minutes walking test, and Berg Balance Scale. Here we will look only at the data from the Berg Balance Scale, which was completely performed by 7 out of the 11 participants.

We compared the maximum score on games played on the Moto tiles of each individual with the score of the posttest (Berg Balance Scale).

Figure 1 shows the game score (each column accumulated maximum game score of the three games) and the score of the Berg Balance posttest on the x-axis.

Even if the data here is very small from such an initial pilot study, it is interesting to speculate whether there can be a correlation between the game score and the health score (such as represented with e.g. Berg Balance test score). For instance, the cut-point for low risk of falling and medium risk of falling in Berg Balance test is 40, and cut-off point 45 has been suggested for multiple fall risk and assistive need, so with a much larger data set it would be interesting to see if some game score could correlate to a Berg score above or below such cut-points.

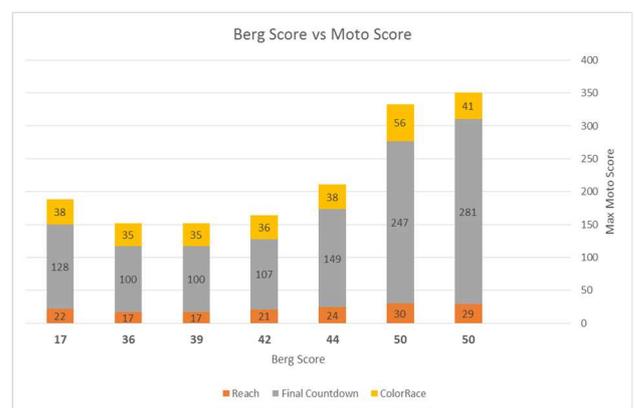


Fig 1. Relationship between Berg score (posttest) and maximum Moto game score for 7 older adults.

4. Discussion and Conclusion

It is important to notice that there may be habituation to the games, so one has to be careful in using game score as a predictor for the general health status (though one has to distinguish between habituation to the tool (i.e. Moto tiles) and habituation to the activity (i.e. game) that may change), and much more work is needed. Nevertheless, it is interesting with the small indicators of relationship between game score and measurements from the personal health technology (heart rate and steps) representing the short-term effect, and the standard balancing test representing the long-term effect. This pilot study should therefore open up for much more thorough studies on such potential relationships, their nature and their relevance.

The relationship shown between game design and set-up, heart rate and steps suggest that such physiological measurements can be used in the design process to design physical interactive games with different qualities. Some designs may be more effective than others, and they may be qualified, tested and verified for their effect as has been indicated in the work presented here.

Previously, it has also been shown that children's heart rate can be captured on a prototype playware playground, and that children's notion of entertainment correlates highly with their average heart rate during the game [13].

Importantly, the interaction was mediated by the Moto tiles acting as a playware, which motivated the participants to play for their own enjoyment. In this study, the personal health technology in the form of Fitbit acted as a measuring tool, and it was the playware (Moto tiles), which acted as the persuasive technology.

Acknowledgement

The experiments with Fitbit measurements of Moto tiles games were performed by Yancy Liu. The pilot study with older adults in Lyngby municipality was performed as part of the EU project REACH: Responsive Engagement of the Elderly Promoting Activity and Customized Healthcare (thanks to J. Jessen, DTU Management (Prof. Andersen), Lyngby Municipality, and project partners).

References

1. B. J. Fogg "Persuasive technology: using computers to change what we think and do." *Ubiquity* 2002. December (2002): 5.
2. J. B. Hirsh, S. K. Kang, & G. V. Bodenhausen "Personalized persuasion: Tailoring persuasive appeals to recipients' personality traits." *Psychological science*, 23(6), 578-581, 2012.
3. R. M. Ryan & E. L. Deci. Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary educational psychology*, 25(1), 54-67, 2000.
4. J. Hart, M. Stasson, J. M. Mahoney, and P. Story. The big five and achievement motivation: Exploring the relationship between personality and a two-factor model of motivation. *Individual Differences Research*. 5. 267-274, 2007
5. J. Huizinga. *Homo Ludens* IIs 86 (Vol. 3). Routledge. 2014
6. C. Jessen, & H. H. Lund, H. H. On play forces, play dynamics and playware. Unpublished manuscript, 2009.
7. H. H. Lund, and C. Jessen, "Playware - Intelligent technology for children's play," Technical Report TR-2005-1, June, Maersk Institute, University of Southern Denmark, 2005.
8. H.H. Lund, T. Klitbo, and C. Jessen, "Playware Technology for Physically Activating Play", *Artificial Life and Robotics Journal*, 9:4, 165-174, 2005
9. H. H. Lund, "Play for the Elderly - Effect Studies of Playful Technology," in *Human Aspects of IT for the Aged Population. Design for Everyday Life*. (LNCS Vol. 9194, pp 500-511, Springer-Verlag, 2015)
10. H. H. Lund, and J. D. Jessen, "Effects of short-term training of community-dwelling elderly with modular interactive tiles," *GAMES FOR HEALTH: Research, Development, and Clinical Applications*, 3(5), 277-283, 2014.
11. <http://www.moto-tiles.com> (checked: 28/11/2017)
12. <http://www.moto-tiles.com/video.php?L=en&s=games> (checked 28/11/2017)
13. G.N. Yannakakis, J. Hallam, H.H. Lund "Capturing entertainment through heart-rate dynamics in the playware playground" *Proceedings of the 5th International Conference on Entertainment Computing Lecture Notes in Computer Science*, vol. 4161, Springer, Cambridge, UK, pp. 314-317, 2006.