A Playful Smartphone-based Self-regulation Training for the Prevention and Treatment of Child and Adolescent Obesity: Technical Feasibility and Perceptions of Young Patients

Tobias Kowatsch[a,b,c], Chen-Hsuan (Iris) Shih[a], Yanick X. Lukic[a], Olivia C. Keller[a], Katrin Heldt[d], Dominique Durrer[e], Aikaterini Stasinaki[d,g], Dirk Büchter[d], Björn Brogle[d], Nathalie Farpour-Lambert[f] and Dagmar l'Allemand-Jander[d,g]

[a]*Centre for Digital Health Interventions, Department of Management, Technology and Economics, ETH Zurich, Zurich, Switzerland*
[b]*Centre for Digital Health Interventions, Institute of Technology Management, University of St.Gallen, St.Gallen, Switzerland*
[c]*Saw Swee Hock School of Public Health, National University of Singapore, Singapore*
[d]*Adolescent Medicine, Children's Hospital of Eastern Switzerland, St.Gallen, Switzerland*
[e]*Child and Youth School Health Service, Department of Education and Youth, Vevey, Switzerland*
[f]*Service of Endocrinology, Diabetology, Nutrition and Therapeutic Patient Education, Department of Medicine, University Hospitals of Geneva, Geneva, Switzerland*
[g]*Pediatric Endocrinology, Children's Hospital of Eastern Switzerland, St.Gallen, Switzerland*

Abstract
Effective interventions for the prevention and treatment of child and adolescent obesity play an important role in reducing the global health and economic burden of non-communicable diseases. Although multi-component interventions targeting various health behaviors are deemed promising, evidence for their effectiveness is still limited. Self-regulation seems to be a relevant working mechanism in this regard. Therefore, we propose a playful, smartphone-based self-regulation training that also utilizes the health benefits of a slow-paced breathing exercise. The mobile app uses the microphone of the smartphone to detect breathing sounds (e.g. inhalation, exhalation) and translates these sounds into a visual biofeedback on the smartphone screen. The design and evaluation of a very first prototype is described in this interdisciplinary work of obesity experts, clinical psychologists, young patients, and computer scientists. The apps' breathing detection module uses a random forest tree for quasi real-time classification of the incoming audio samples and biofeedback generation. A study with 11 children and adolescents with obesity was conducted to assess the prototype. Results indicate overall positive evaluations and suggestions for improvement. Implications and limitations are discussed, and an outlook on future work is provided.

Keywords
human-computer interaction, self-regulation, digital health intervention, biofeedback, breathing training, breathing detection

1. Introduction

Non-communicable diseases (NCDs), such as cardiovascular diseases or mental disorders, are the leading cause of death worldwide, contributing to 73% of deaths [1]. NCDs also lead to a significant financial burden [2, 3], for example, up to 90% of all health care spending in the U.S. [4].

To address this important problem, health interventions must target adverse health behaviors such as malnutrition, physical inactivity and resulting metabolic risk factors, for example, obesity [5]. The earlier in life effective interventions are delivered, the lower the future financial burden of NCDs and the more likely the uptake of health-promoting behaviors is due to heightened neuroplasticity and cognitive flexibility in children and adolescents [6, 7]. These efforts are especially important as child and adolescent obesity has increased substantially worldwide [8], while recent systematic reviews found only low to moderate evidence for effective interventions [9, 10].

Although evidence suggests multi-component interventions that target, for example, physical activity and diet, underlying mechanisms for why and for whom they work are still under investigation [10]. Self-regulation has been proposed as an important mechanism in child health [11] as it refers to the "cognitive and behavioral processes through which an individual maintains levels of emotional, motivational, and cognitive arousal that

Joint Proceedings of the ACM IUI 2021 Workshops, April 13–17, 2021, College Station, USA
tkowatsch@ethz.ch (T. Kowatsch);
dagmar.lallemand@kispisg.ch (D. l'Allemand-Jander)
https://www.c4dhi.org/ (T. Kowatsch)
0000-0001-5939-4145 (T. Kowatsch); 0000-0002-2576-6569 (Y. X. Lukic); 0000-0001-8761-8214 (O. C. Keller); 0000-0001-6478-7269 (N. Farpour-Lambert); 0000-0003-3144-3907 (D. l'Allemand-Jander)

are conducive to positive adjustment and adaptation, as reflected in positive social relationships, productivity, achievement, and a positive sense of self." [12, p. 900] For instance, obese children, require self-regulation skills to resist the urge to eat unhealthy food. In this context, it was demonstrated that children who have experienced loss of control eating report a higher use of maladaptive strategies for the regulation of emotions than children without a history of loss of control eating [13]. Similarly, another study identifies emotional regulation as the moderator for the relationship between perceived stress and emotional eating [14].

Furthermore, a systematic review indicates that self-regulation skills are among the best predictors of outcomes in obesity interventions in adults [15]. Another study with a representative sample of U.S. children not only found a link between self-regulation and the risk of obesity, but further identified that this link is stronger between boys and girls [16]. Moreover, a recent systematic review found that interventions with self-regulation interventions can be effective in children and adolescents, with possible health benefits [17]. All in all, self-regulation skills represent a relevant target in multi-component interventions for the prevention and treatment of child and adolescent obesity.

To this end, we propose a playful self-regulation training for children and adolescents. The training is delivered via a mobile app and focuses on a breathing exercise. The app uses the microphone of a smartphone to detect inhalation, exhalation, silence and noisy sounds to then visually guide the user to perform a slow-paced breathing training. With the help of the visual biofeedback, breathing can be adjusted with the overall goal to improve self-regulation skills. A conceptual overview of the training is depicted in Fig. 1.

After a brief overview of related work in the next section, we describe the design of a very first prototype and the evaluation procedure targeting obese children and adolescents. We then present and discuss the results and conclude with a summary and outlook on future work.

2. Related Work

Slow-paced breathing was chosen in this investigation because it is not only a common self-regulation tool [e.g., 18, 19, 20, 21, 22] but also shows positive "side" effects on cardiac functioning and mental well-being [23, 24, 25].

The work of Carlier et al. [26] is similar to our training as they implemented a mobile game that uses the microphone of a smartphone to detect an "ommm"-sound to then visually guide children through a breathing exercise. They tested their prototype with three children suffering from autism spectrum disorder. However, results indicated no effects on stress reduction or technology

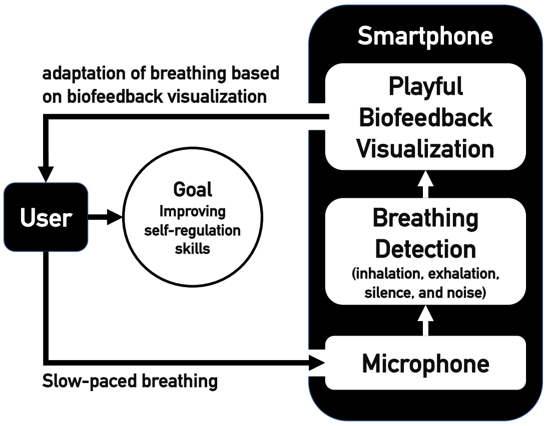

Figure 1: Concept of the self-regulation training

acceptance.

Empirical results of another related work by Shih et al. [27] were more promising. They implemented a similar self-regulation training and found positive effects on physiological outcomes and technology acceptance. However, the authors tested their prototype with 19 healthy university students and thus, these findings may not translate to children and adolescents. Another limitation of this study is that the authors employed a breathing detection model based on an attention-based long short-term memory model in conjunction with a preceding convolutional neural network which may not run on older smartphones with limited computational power.

Another study by Hunter et al. [28] investigated whether a slow-paced breathing training with a mobile app that features heart rate variability biofeedback affects the recovery from an artificial stressor. They found that the app had a significant effect on salivary alpha amylase recovery while not showing a significant effect on cortisol recovery or self-reported stress recovery. Technically, the app does not detect breathing but the heartbeat from the smartphone's rear camera in conjunction with the flashlight. Thus, the app can present the breathing exercise's impact on the user's heart rate variability. However, the heart rate variability is not consciously controlled and its measurement is time-delayed. Consequently, the breathing training does not allow responsive user interaction.

3. Methods

The design and evaluation of the smartphone-based self-regulation training was collaboratively carried out by an interdisciplinary team of computer scientists, obese children and adolescents as well as several obesity experts including physicians, psychotherapists, and diet and sport experts from a children's hospital. The project described in this work was also approved by the local ethics board. The specifics of the design and evaluation phases are outlined in the following sections.

3.1. Design of the Mobile App

3.1.1. User Interface

A focus group discussion with 11 young patients, moderated by obesity experts, was conducted as a first step to gather design requirements for the self-regulation training. In response to that discussion, a first conceptual draft of the user interface was developed. The overall goal of the self-regulation training was to "move" a boat sailing on an ocean towards an isle, far far away, with the help of slow-paced breathing. Specifically, exhalation should imitate wind that blows the boat forward while inhalation should imitate the collection of wind energy for the next breathing cycle. A draft of this idea is depicted in Fig. 2 which also shows a distance-to-destination indicator on the bottom and speech bubbles with additional breathing instructions.

Based on feedback from the obesity experts and young patients, several elements were dropped and revised to further streamline the user interface. For example, the distance indicator at the bottom and the wind energy indicator on the right-hand side were removed so that users could better focus better on the sailboat and its movements toward the destination isle. Further, the speech bubbles were replaced by a digital coach at the top of the screen who had the role to "guide" users through the training. Moreover, moving clouds were introduced to support the boat movements towards the destination isle and to provide also a visual feedback for inhalation sounds. In the latter "inhalation" case, clouds gathered together at the center of the screen while they moved apart when inhaling. The high-level biofeedback logic was also defined collaboratively among young patients, obesity experts and computer scientists. It is outlined in Algorithm 1. A prototype of the graphical user interface was then implemented for the Android operating system. Fig. 3 shows a screenshot of that interface.

3.1.2. Instructional Video Clip

To ensure consistent and evidence-based instructions on how to perform a slow-paced breathing training, an instructional video clip was produced with the help of the involved obesity experts. This video clip would be presented to the user before she or he would perform the self-regulation training with the app for the very first time. The clip explains in ca. 30s how a deep abdominal breathing is conducted and instructs the audience to inhale through the nose and to exhale through the mouth while performing circa six breath cycles per minute [25].

Figure 2: Draft of the App's User Interface

To match the style of the user interface of the app, the video clip employs a comic-like character and elements of the mobile user interface (e.g. ocean, sailboat and clouds). The resulting instructional video clip was shown to four young patients who were then asked to perform the communicated slow-paced breathing. The breathing technique was assessed by the obesity experts according to the guidelines communicated through the video clip and deemed appropriate.

3.1.3. Breathing Detection

The overall goal of the breathing detection module of the self-regulation training is to process audio signals in quasi real time to distinguish between inhalation, exhalation, silence, and noise captured by a smartphone's microphone.

In a first step, we aimed at assessing the technical feasibility of this approach and built a database of audio samples. Due to limited access to young patients and to reduce the burden of them as patients, as well as due to the feasibility character of this investigation, we decided

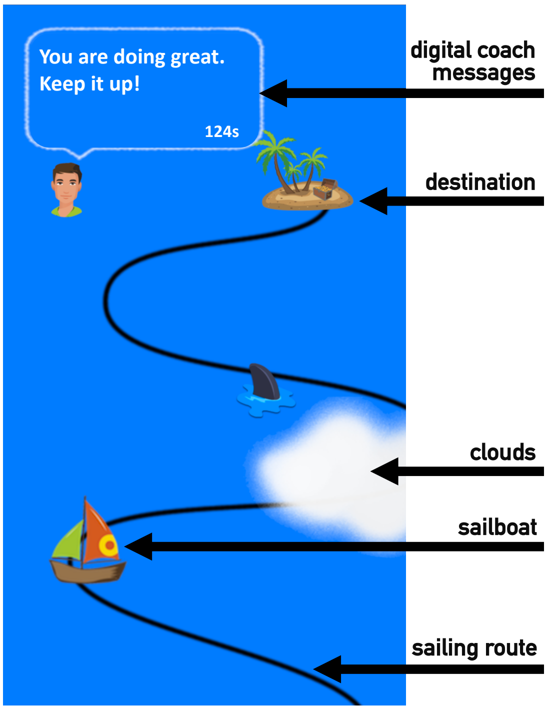

Figure 3: Annotated Screenshot of the App

Algorithm 1: Biofeedback Logic

Input: detection = {inhalation, exhalation, silence, noise}
Output: biofeedback = {clouds, sailboat, and digital coach message}

```
while destination not reached do
    switch detection do
        case inhalation do
            clouds gather together
        case exhalation do
            clouds expand
            sailboat moves towards destination
            digital coach provides positive
              feedback
        case silence do
            digital coach motivates user to inhale
        case noise do
            digital coach recommends to reduce
              surrounding noise
    end
end
```

to collect audio samples from four doctoral students (2 females; all between 25 and 27 years old). We asked the doctoral students to sit comfortably in a chair in their office and perform a slow-paced breathing exercise for three minutes according to the instructions of the video clip described in Section 3.1.2. The audio was recorded with a Samsung Galaxy S6 Edge through a customized app that uses the Android AudioRecord API (PCM, 16bit, 44.1 kHz). The distance to the smartphone for these recordings was about 20cm, a distance we found optimal for the breathing exercise, too. One co-author listened to the resulting recordings and manually cut them into separate audio files labeling them as *inhalation*, *exhalation*, or *silence*. To collect additional samples for silence and noise, the same smartphone was used to record sounds in an office. This resulted in audio samples of passing cars and streetcars or the speech of office workers, which were manually marked as *noise*. Silent audio samples were manually labeled as *silence*. The data collection resulted in around 28,000 audio samples of 80ms length. This length was chosen as it represented the minimum buffer size that could be acquired through the Android audio engine at the time of implementation.

In a second step, we calculated for each sample the first 13 Mel-frequency cepstral coefficients [29] with a window size of 25ms and a 50% overlap. The coefficients were supplemented with four descriptive statistical measures. From the time-domain we used the mean, variance, and maximum of the raw audio amplitude and from the frequency-domain the peak frequency amplitude.

Third, and consistent with prior work that was successful in detecting breathing patterns [30], a Random Forest model was used with 100 trees, which was empirically found to result in the best prediction performance for our data set.

Since our audio database was relatively small compared to related work [e.g., 27] and to prevent our model from over-fitting, we applied k-fold cross-validation for training and validation. We trained the random forest model using the WEKA library. First, we applied a 80/20 training to test split over all four participants. Second, we conducted 10-fold cross-validation on the training data. Third, we tested the best model on the test set. The performance of the model on the test set is reported in Table 1. The results indicate that the trained model is able to appropriately differentiate between the four classes for the breathing of known individuals.

Finally, the trained random forest model was integrated into the mobile app using the WEKA Android API. The feature extraction in the app was reproduced using Java in conjunction with the audio processing library OpenIMAJ 1.3.9. The resulting predictions of the incoming data would then trigger the animations of the user interface outlined in Algorithm 1.

Table 1
Offline Performance of the Random-Forest Breathing Detection Algorithm

Class	TPR	FPR	PRE	F1-Score	AUC-ROC
Inhalation	0.942	0.012	0.955	0.949	0.990
Exhalation	0.940	0.007	0.977	0.948	0.992
Silence	0.963	0.023	0.931	0.947	0.994
Noise	0.980	0.021	0.954	0.967	0.996
All 4 classes	0.954	0.016	0.954	0.955	0.994

Note: true positive rate (TPR), false positive rate (FPR), precision (PRE), area under the curve receiver operating characteristic (AUC-ROC)

3.2. Evaluation Procedure

A study with obese children and adolescents was conducted in the children's hospital of the participating obesity experts to assess the technical feasibility and perceptions of the self-regulation training. The procedure was as follows.

First, patients were instructed to watch the educational breathing video clip and to perform the breathing exercise without the app. Obesity experts provided feedback on their breathing to assure a correct technique.

In a second step, obesity experts handed over the Android smartphone, the same model used for data collection (i.e. the Samsung S6 Edge), with the self-regulation training app to the patients. The experts then explained the purpose of the app and its visual feedback logic.

Finally, obesity experts asked the patients to perform the app's slow-paced breathing exercise. The patients' goal was to "sail" the sailboat to the destination. During the exercise and for safety purposes, obesity experts observed the patients and intervened in case of any adverse breathing activity. Moreover, they noted down whether the goal was achieved and the sailboat reached the destination, and how long it took the patients to get there.

Afterwards, the patients received a questionnaire that allowed them to assess the app. Constructs of interest were adopted from technology acceptance research [31, 32] and included perceived ease of use, perceived enjoyment, expected usefulness at home, intention to use and perceived relaxation after use. Consistent with prior work [33, 34], a single item per construct was used to reduce the burden of the young patients. All items were anchored on 7-point Likert scales ranging from strongly disagree (-3) to strongly agree (3). All constructs and item wordings are listed in Table 2. Finally, patients were asked to write down any suggestions they may have to improve the app.

4. Results

Overall, 8 female and 3 male young 9-16 year-old (M = 12.6, SD = 2.4) children and adolescents with obesity participated in the study. All patients were able to reach the goal set by the training app in 40 to 120 seconds. However, obesity experts observed that due to the playful character of the app, three subjects started to perform an adverse breathing pattern (e.g. hyperventilation or extensive and long exhalation), motivated by the goal to bring the sailboat as quickly as possible to its destination, despite being instructed otherwise.

The descriptive statistics of the patients' self-reported perceptions of the participating patients are listed in Table 2 and corresponding boxplots with raw responses are shown in Fig. 4. The high average mean values for all constructs indicate that the patients found the training app easy to use and conducive to relaxation at home. Additionally, the patients reported enjoying its actual usage and indicated that they could even imagine using the app-based training every day. Finally, patients shared that they were able to relax using the app. One-sample sign tests confirmed these results as the self-reported scores all lie significantly above the neutral scale value of zero.

The qualitative feedback indicated that the digital coach moderating the self-regulation exercise should be customizable, for example, regarding their outfit. Moreover, the training session was perceived as too short and thus, it was suggested to extend the journey with the sailboat. It was also suggested to add further elements to the ocean scene, for example, additional milestones such as smaller isles or surface marker buoys as sub-ordinate targets that would trigger points when passing by with the sailboat. Interestingly, there were some enquiries into whether the training app was available on Apple's iOS platform, which indicated further interest in the training app.

Overall, the qualitative feedback confirmed the positive quantitative results presented above.

Table 2
Perceptions of 11 Young Children and Adolescents with Obesity

Construct	Scale item wording	Mean	SD	95% CI	p-value
Perceived ease of use	I found it easy to blow the sailboat to the next island.	2.64	0.67	[2.21 3.00]	$< 0.001^{***}$
Perceived enjoyment	I enjoyed the breathing exercise.	2.73	0.65	[3.00 3.00]	$< 0.001^{***}$
Expected usefulness at home	I could imagine the exercise helping me relax at home.	1.55	1.04	[1.00 3.00]	0.002^{**}
Intention to use	I can imagine doing this exercise every day.	2.27	1.27	[2.00 3.00]	0.006^{**}
Perceived relaxation	With this exercise I could relax well just now.	1.45	1.29	[0.00 3.00]	0.008^{**}

Note: confidence interval (CI); p < .001 = *** and p < .01 = ** for one-sample sign tests with 0 as test value and alternative hypothesis being greater as 0; 7-point Likert scales were anchored from strongly disagree (-3) to strongly agree (3)

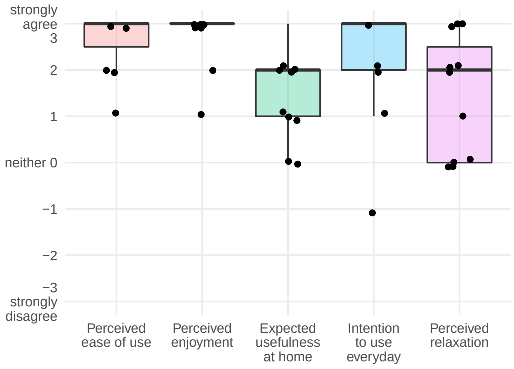

Figure 4: Boxplots and Answers of Self-reported Perceptions of 11 Young Children and Adolescents with Obesity

5. Discussion

The current work presented a playful, smartphone-based self-regulation training that was collaboratively developed by an interdisciplinary team of obesity experts, clinical psychologists, children and adolescents with obesity, as well as computer scientists. The evaluation of the training with 11 young obesity patients showed the technical feasibility, as all patients were able to bring the sailboat to its destination. Moreover, self-reports of the participating patients resulted in overall positive technology assessments and various suggestions for improvement were provided.

However, the evaluation also resulted in relevant insights regarding potential side effects. First, the playful biofeedback visualization motivated patients to adopt a breathing technique that could lead to dizziness due to hyperventilation or prolonged periods of exhalation. A biofeedback visualization that offers time-restricted inhalation and exhalation windows may overcome this problem. That is, the sailboat could only be moved forward during a pre-defined time window that promotes a "healthy" slow-paced breathing [27]. Another potential side effect promoted by the playful nature of the self-regulation training might be smartphone addiction [35, 36]. Limiting the number of exercises per day could be a solution in this regard. Finally, adding additional playful elements as suggested by the young patients raises the question to which degree the experiential effect of the app can potentially cancel out the development of self-regulation skills and other health benefits of slow-paced breathing such as calming down or strengthening the cardiac system. Related work provides first evidence that both experiential and instrumental effects can coexist [27, 37].

This work has also several limitations. First, the offline performance of the detection model is based on a small sample of only four doctoral students and not on breathing data from the target population. Both aspects, the small sample size resulting in low variance of breathing sounds and the mismatch of model development with population A and assessment by population B, limit the generalizability of the findings. Second, the training and test sets were collected in the same context, i.e. the same recording environment and smartphone model, and contain breathing sounds from the same individuals. Consequently, the detection performance for unknown individuals, other devices, or different environments remains unknown. Third, the data collection with respect to noisy environments was limited to only one specific environment (the office). Fourth, only one specific biofeedback theme was evaluated, i.e. the "ocean-and-sailboat" theme, and thus, it is open to which degree visual elements may have an impact on the effects of the self-regulation training. Third, the cross-sectional study setting in the children's hospital does not allow to draw any conclusions on long-term engagement with the app. Finally, the evaluation procedure did not contain any validated instrument to assess self-regulation and thus, no conclusions can be drawn in this regard, too.

6. Summary and Future Work

We highlighted the relevance of self-regulation mechanisms in interventions targeting the prevention and treatment of obesity in children and adolescents. We proposed, implemented and evaluated a breathing-based self-regulation training with young patients affected by obesity.

However, the current work also points towards opportunities for upcoming research. First and foremost, future work may focus on environment-agnostic breathing detection that generalizes among individuals, smartphones, headsets, and various "distracting" soundscapes. Second, micro-randomized trials may be conducted to assess an optimal balance of experiential vs instrumental interface designs. Third, guided-biofeedback interfaces may limit cheating in breathing, which, in turn, could reduce any adverse breathing patterns. And finally, the impact of self-regulation training on self-regulation skills and relevant lifestyle behavior should be assessed in longitudinal field studies that target the prevention and treatment of child and adolescents obesity.

Acknowledgments

We would like to thank the CSS Insurance and the Swiss National Science Foundation for their support through grants 159289 and 162724.

References

[1] G. A. Roth, D. Abate, K. H. Abate, S. M. Abay, C. Abbafati, N. Abbasi, H. Abbastabar, F. Abd-Allah, J. Abdela, A. Abdelalim, I. Abdollahpour, R. S. Abdulkader, H. T. Abebe, M. Abebe, Z. Abebe, A. N. Abejie, S. F. Abera, O. Z. Abil, H. N. Abraha, A. R. Abrham, et al., Global, regional, and national age-sex-specific mortality for 282 causes of death in 195 countries and territories, 1980-2017: a systematic analysis for the global burden of disease study 2017, Lancet 392 (2018) 1736–1788. doi:10.1016/s0140-6736(18)32203-7.

[2] D. Newman, M. Tong, E. Levine, S. Kishore, Prevalence of multiple chronic conditions by u.s. state and territory, 2017, PLOS ONE 15 (2020) e0232346. doi:10.1371/journal.pone.0232346.

[3] A. Murphy, B. Palafox, M. Walli-Attaei, T. Powell-Jackson, etal., The household economic burden of non-communicable diseases in 18 countries, BMJ Global Health 5 (2020) e002040. doi:10.1136/bmjgh-2019-002040.

[4] M. B. Christine Buttorff, Teague Ruder, Multiple chronic conditions in the united states, 2017. URL: https://www.rand.org/pubs/tools/TL221.html. doi:10.7249/TL221.

[5] WHO, Global action plan for the prevention and control of noncommunicable diseases 2013–2020, Report, World Health Organization, 2020. URL: http://apps.who.int/iris/bitstream/handle/10665/94384/9789241506236_eng.pdf.

[6] F. Y. Ismail, A. Fatemi, M. V. Johnston, Cerebral plasticity: Windows of opportunity in the developing brain, European Journal of Paediatric Neurology 21 (2017) 23–48. doi:10.1016/j.ejpn.2016.07.007.

[7] F. Buttelmann, J. Karbach, Development and plasticity of cognitive flexibility in early and middle childhood, Frontiers in Psychology 8 (2017). doi:10.3389/fpsyg.2017.01040.

[8] T. Lobstein, R. Jackson-Leach, M. L. Moodie, K. D. Hall, S. L. Gortmaker, B. A. Swinburn, W. P. T. James, Y. Wang, K. McPherson, Child and adolescent obesity: part of a bigger picture, Lancet 385 (2015) 2510–20. doi:10.1016/s0140-6736(14)61746-3.

[9] T. Brown, T. H. Moore, L. Hooper, Y. Gao, A. Zayegh, S. Ijaz, M. Elwenspoek, S. C. Foxen, L. Magee, C. O'Malley, E. Waters, C. D. Summerbell, Interventions for preventing obesity in children, Cochrane Database Syst Rev 7 (2019) Cd001871. doi:10.1002/14651858.CD001871.pub4.

[10] L. J. Ells, K. Rees, T. Brown, E. Mead, L. Al-Khudairy, L. Azevedo, G. J. McGeechan, L. Baur, E. Loveman, H. Clements, P. Rayco-Solon, N. Farpour-Lambert, A. Demaio, Interventions for treating children and adolescents with overweight and obesity: an overview of cochrane reviews, International Journal of Obesity 42 (2018) 1823–1833. doi:10.1038/s41366-018-0230-y.

[11] A. L. Miller, A. N. Gearhardt, E. M. Fredericks, B. Katz, L. F. Shapiro, K. Holden, N. Kaciroti, R. Gonzalez, C. Hunter, J. C. Lumeng, Targeting self-regulation to promote health behaviors in children, Behaviour Research and Therapy 101 (2018) 71–81. doi:10.1016/j.brat.2017.09.008.

[12] C. Blair, A. Diamond, Biological processes in prevention and intervention: The promotion of self-regulation as a means of preventing school failure, Development and Psychopathology 20 (2008) 899–911. doi:10.1017/S0954579408000436.

[13] J. Czaja, W. Rief, A. Hilbert, Emotion regulation and binge eating in children, Int J Eat Disord 42 (2009) 356–62. doi:10.1002/eat.20630.

[14] E. Aparicio, J. Canals, V. Arija, S. de Henauw, N. Michels, The role of emotion regulation in childhood obesity: implications for prevention and treatment, Nutrition Research Reviews 29 (2016) 17–29. doi:10.1017/S0954422415000153.

[15] P. J. Teixeira, E. V. Carraça, M. M. Marques, H. Rutter, J.-M. Oppert, I. de Bourdeaudhuij, J. Lakerveld, J. Brug, Successful behavior change in obesity interventions in adults: a systematic review of self-regulation mediators, BMC Med 13 (2015) 84. doi:10.1186/s12916-015-0323-6.

[16] S. E. Anderson, R. C. Whitaker, Association of

self-regulation with obesity in boys vs girls in a us national sample, JAMA Pediatrics 172 (2018) 842–850. doi:10.1001/jamapediatrics.2018.1413.

[17] A. Pandey, D. Hale, S. Das, A.-L. Goddings, S.-J. Blakemore, R. M. Viner, Effectiveness of universal self-regulation–based interventions in children and adolescents: A systematic review and meta-analysis, JAMA Pediatrics 172 (2018) 566–575. doi:10.1001/jamapediatrics.2018.0232.

[18] M. Martin, M. Seppa, P. Lehtinen, T. Toro, Breathing as a Tool for Self-Regulation and Self-Reflection, Routledge, London, UK, 2016. doi:10.4324/9780429472572.

[19] Y.-Y. Tang, Y. Ma, J. Wang, Y. Fan, S. Feng, Q. Lu, Q. Yu, D. Sui, M. K. Rothbart, M. Fan, M. I. Posner, Short-term meditation training improves attention and self-regulation, Proceedings of the National Academy of Sciences 104 (2007) 17152–17156. doi:10.1073/pnas.0707678104.

[20] N. Harvey, Mindful little yogis: self-regulation tools to empower kids with special needs to breath and relax, Singing Dragon, London, UK, 2018.

[21] Z. Wang, A. Parnandi, R. Gutierrez-Osuna, Biopad: Leveraging off-the-shelf video games for stress self-regulation, IEEE Journal of Biomedical and Health Informatics 22 (2018) 47–55. doi:10.1109/JBHI.2017.2671788.

[22] A. L. Eva, N. M. Thayer, Learning to breathe: A pilot study of a mindfulness-based intervention to support marginalized youth, Journal of Evidence-Based Complementary & Alternative Medicine 22 (2017) 580–591. doi:10.1177/2156587217696928.

[23] M. C. Schumer, E. K. Lindsay, J. D. Creswell, Brief mindfulness training for negative affectivity: A systematic review and meta-analysis, Journal of Consulting and Clinical Psychology 86 (2018) 569–583. doi:10.1037/ccp0000324.

[24] A. Zaccaro, A. Piarulli, M. Laurino, E. Garbella, D. Menicucci, B. Neri, A. Gemignani, How breath-control can change your life: A systematic review on psycho-physiological correlates of slow breathing, Frontiers in Human Neuroscience 12 (2018). doi:10.3389/fnhum.2018.00353.

[25] M. E. B. Russell, A. B. Scott, I. A. Boggero, C. R. Carlson, Inclusion of a rest period in diaphragmatic breathing increases high frequency heart rate variability: Implications for behavioral therapy, Psychophysiology 54 (2017) 358–365. doi:10.1111/psyp.12791.

[26] S. Carlier, S. Van der Paelt, F. Ongenae, F. De Backere, F. De Turck, Using a serious game to reduce stress and anxiety in children with autism spectrum disorder, in: Proceedings of the 13th EAI International Conference on Pervasive Computing Technologies for Healthcare, PervasiveHealth'19, Association for Computing Machinery, New York, NY, USA, 2019, p. 452–461. doi:10.1145/3329189.3329237.

[27] C.-H. Shih, N. Tomita, Y. X. Lukic, A. H. Reguera, E. Fleisch, T. Kowatsch, Breeze: Smartphone-based acoustic real-time detection of breathing phases for a gamified biofeedback breathing training, Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 3 (2019) Article 152. doi:10.1145/3369835.

[28] J. F. Hunter, M. S. Olah, A. L. Williams, A. C. Parks, S. D. Pressman, Effect of brief biofeedback via a smartphone app on stress recovery: Randomized experimental study, JMIR Serious Games 7 (2019) e15974. doi:10.2196/15974.

[29] S. B. Davis, P. Mermelstein, Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences, IEEE Transactions on Acoustics, Speech, and Signal Processing 28 (1980) 357–366. doi:10.1109/TASSP.1980.1163420.

[30] T. Rosenwein, E. Dafna, A. Tarasiuk, Y. Zigel, Detection of breathing sounds during sleep using non-contact audio recordings, in: 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2014, pp. 1489–1492. doi:10.1109/EMBC.2014.6943883.

[31] A. Kamis, M. Koufaris, T. Stern, Using an attribute-based decision support system for user-customized products online: An experimental investigation, MIS Quarterly 32 (2008) 159–177. doi:10.2307/25148832.

[32] F. D. Davis, Perceived usefulness, perceived ease of use, and user acceptance of information technology, MIS Quarterly 13 (1989) 319–339. doi:10.2307/249008.

[33] T. Kowatsch, D. Volland, I. Shih, D. Rüegger, F. Künzler, F. Barata, A. Filler, D. Büchter, B. Brogle, K. Heldt, P. Gindrat, N. Farpour-Lambert, D. l'Allemand, Design and Evaluation of a Mobile Chat App for the Open Source Behavioral Health Intervention Platform MobileCoach, Springer, Berlin; Germany, 2017, pp. 485–489. doi:10.1007/978-3-319-59144-5_36.

[34] T. Kowatsch, W. Maass, I. P. Cvijikj, D. Büchter, B. Brogle, A. Dintheer, D. Wiegand, D. Durrer, R. Xu, Y. Schutz, D. l. Dagmar, Design of a health information system enhancing the performance of obesity expert and children teams, in: Proc 22nd European Conference on Information Systems (ECIS), Tel Aviv, Israel, 2014.

[35] S. Haug, R. P. Castro, M. Kwon, A. Filler, T. Kowatsch, M. P. Schaub, Smartphone use and smartphone addiction among young people in switzerland, Journal of Behavioral Addictions 4 (2015) 299–307. doi:10.1556/2006.4.2015.037.

[36] M. Kwon, D.-J. Kim, H. Cho, S. Yang, The smartphone addiction scale: Development and validation of a short version for adolescents, PLOS ONE 8 (2014) e83558. doi:10.1371/journal.pone.0083558.

[37] Y. X. Lukic, C.-H. I. Shih, A. H. Reguera, A. Cotti, E. Fleisch, T. Kowatsch, Physiological responses and user feedback on a gameful breathing training app: Within-subject experiment, JMIR Serious Games 9 (2021). doi:10.2196/22802.