



# Gamification of Movement Exercises in Rehabilitation and Prevention: A Framework for Smart Training in AI-Based Exergames

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**Abstract.** Activities for rehabilitation and prevention are often lengthy and associated with pain and frustration. Their playful enrichment (hereafter: gamification) can counteract this, resulting in so-called “exergames”. However, in contrast to games designed solely for entertainment, the increased motivation and immersion in gamified training can lead to a reduced perception of pain and thus to health deterioration. Therefore, it is necessary to monitor activities continuously. However, only an AI-based system able to generate autonomous interventions could vacate the therapists’ costly time and allow better training at home. An automated adjustment of the movement training’s difficulty as well as individualized goal setting and control are essential to achieve such autonomy. This article’s contribution is two-fold: (1) We portray the potentials of gamification in the health area. (2) We present a framework for smart rehabilitation and prevention training allowing autonomous, dynamic, and gamified interactions.

**Keywords:** Prevention · Rehabilitation · Gamification · Exergames · Gamified training · Motion monitoring · Affective computing · Artificial intelligence

## 1 Introduction

Rehabilitation measures after accidents or illnesses are often lengthy and frequently associated with pain and frustration. Initially, quickly visible success is motivating. However, with increasing duration, the training discipline decreases due to the slower improvements. The same applies to many preventive measures. A playful enrichment of the training (in the following: gamification) can counteract this development by increasing the fun factor. This idea has been around for a while: already ten years ago Wiemeyer acknowledged that “digital games – in the sense of serious games – in principle have great potential for sports medicine prevention and rehabilitation” [1]. Indeed, the availability of low-cost sensor-based systems for continuous motion recognition has dramatically increased the potential for application in recent years. However, these systems often require continuous therapeutic monitoring on-site and hardly meet the high time

requirements for prevention and rehabilitation measures. Based on the state of the art in the fields of gamification and movement monitoring, we outline the potentials of smart gamified systems, i.e., systems equipped with artificial intelligence, for the healthcare sector. Subsequently, we present the outline of an autonomous, dynamic gamified system for smart rehabilitation and prevention training.

### **1.1 Gamification and Exergames**

Gamification refers to the transfer of elements from (video) games, such as collecting points and leveling up, to “serious” real-world contexts [2]. The introduction of gamified elements gives real-world tasks a playful character. The goal is to use fun to increase motivation in order to work better or at least faster. Following self-determination theory [3], gamification can increase fun and incentive by satisfying the basic psychological needs of autonomy, competence, and relatedness. Gamified environments can promote autonomy by reducing or setting aside the real-world constraints. Also, gamified processes can create a greater degree of variety as well as options and choices, increasing the perceived autonomy [4]. Similarly, the need for self-competence can be met by balancing game difficulty and player skill, as well as providing direct feedback on performance [5, 6].

Several gamification techniques have become established. The number of potential playful elements is large and appeals to users in very different ways: the spectrum ranges from a simple collection of points to telling complex stories. Bartle, for example, distinguishes four types according to different character traits in his basic model [7]: “Achievers” are motivated by points and awards, “Socializers” want to build relationships with other players, “Explorers” want to discover new worlds, and “Killers” are eager to defeat others.

With the advent of game consoles using sensor-based motion control such as the Nintendo Wii (2006) and Microsoft Kinect (2010), it became possible to capture physical activities playfully with comparatively little technical effort. In addition to commercial titles for home training such as Wii Sports (Nintendo 2006), Kinect Sports (Microsoft 2010), or Shape up (Ubisoft 2014), games based on motion sensors were also developed specifically for prevention or rehabilitation. Such training games are called “exergames”, a portmanteau of the words “exercise” and “game”.

### **1.2 Potentials of Gamification in the Health Sector**

Healthcare can highly benefit from gamification. Rehabilitation measures are an obvious example. Patients often suffer from emotional trauma after severe illness or accidents [8]. At the same time, they are expected to overcome arduous physical exertion, often accompanied by pain. Typically, primary motor and cognitive processes must be re-learned through frequent repetition and regular practice over a long time.

However, the daily repetition of repetitive motion sequences is already frustrating for healthy people. Accordingly, several studies conclude that about 65% of the patients do not adhere to the rehabilitation program [9]. As a result, complete rehabilitation is rarely achieved. If the program is carried out from home and without regular observation by a therapist, rehabilitation outcomes are even worse. This problem can be counteracted

with gamification. Playful elements can break the boredom of constant repetition with fun and variety, increasing motivation and thus contribute to the rehabilitation success.

A particular challenge, however, is the balance between motivation and excessive demands. In contrast to regular gaming, where overstress only leads to the loss of virtual life force, excessive movements during training can lead to a deterioration of real-world health up to re-injury. This challenge has not been addressed enough in existing approaches. The use of artificial intelligence (AI) can make a decisive contribution here.

### 1.3 Motion Monitoring

The correct execution of therapeutic and preventive measures is of high importance for the success of treatment. Control of movement execution currently requires the use of well-trained and experienced personnel and is therefore associated with high costs. Current developments in wearable sensor technology, e.g., using “Inertial Measurement Units” (IMUs) and machine learning techniques, allow quantifying the movement and load characteristics of an exercise without therapeutic personnel. These systems are currently developed mainly for use in gait and running analyses [10–12], but in principle, this method can be extended to typical prevention and rehabilitation exercises.

A direct application of movement monitoring comes into play in the context of re-learning or re-learning movements. Re-learning of movements is necessary, for example, after severe progressions in stroke patients or severe spinal injuries. Re-learning of movements is used in gait training to reduce mechanical stress on the knee joint in osteoarthritis patients [13, 14]. However, re-learning movement techniques is also highly important in prevention interventions in sports, such as learning a running technique with a lower risk of suffering overuse injuries [15–17].

In addition to (re)learning to move one’s own body, learning to control the movement on artificial limbs is critical for patients with amputations to regain the ability to interact with the environment and participate in social life. Biofeedback applications already play an essential role in learning to control myoelectrically controlled prostheses [18]. In addition to learning to control the prosthetic system, learning an efficient gait pattern could also be the goal of motion monitoring and gait training in the future. For this purpose, selecting suitable movement parameters and their feedback to the patients is of high importance. Enrichment of these training applications with gamification elements should improve the patients’ adherence to these training methods and enable long-term success.

While learning new movement techniques is often still done today in special facilities by specifically trained staff, it is foreseeable that the use of body-worn (or clothing-integrated) sensor technology will enable stand-alone training using software-based feedback [19, 20]. Permanent feedback of movement execution could further account for fatigue-induced movement technique changes [21–23] or other movement execution adjustments [24]. This feedback should be enriched by gamification methods to maintain motivation and ensure the interventions’ sustainable success.

## 2 Framework of an Autonomous, Dynamic Gamified System for Smart Rehabilitation and Prevention Training

There is a broad consensus that gamification improves the motivation of users in therapeutic and preventive measures. For example, a gamified strength training intervention shows that patients trained with gamification visited the rehabilitation center significantly more often [25]. As stated earlier, this enrichment of the training brings the additional challenge of finding the balance between motivation and overexertion.

Already several years ago, a model for dynamic difficulty adaptation of game-based training applications has been presented [26]. It includes a control circuit (“Multi-level control circuit for exercise configuration and quality control”) that dynamically adjusts the difficulty depending on the measured performance data, starting from a base configuration and a fitness control. The Kinect collected the kinematic data, and the adaptation was made in a simple rule-based system in three levels (easier, normal, or more difficult than usual). However, manual input was required to enter the fitness level and calibrate the system. Therefore, it is explicitly stated that further research is needed for patient-specific dynamic adaptation.

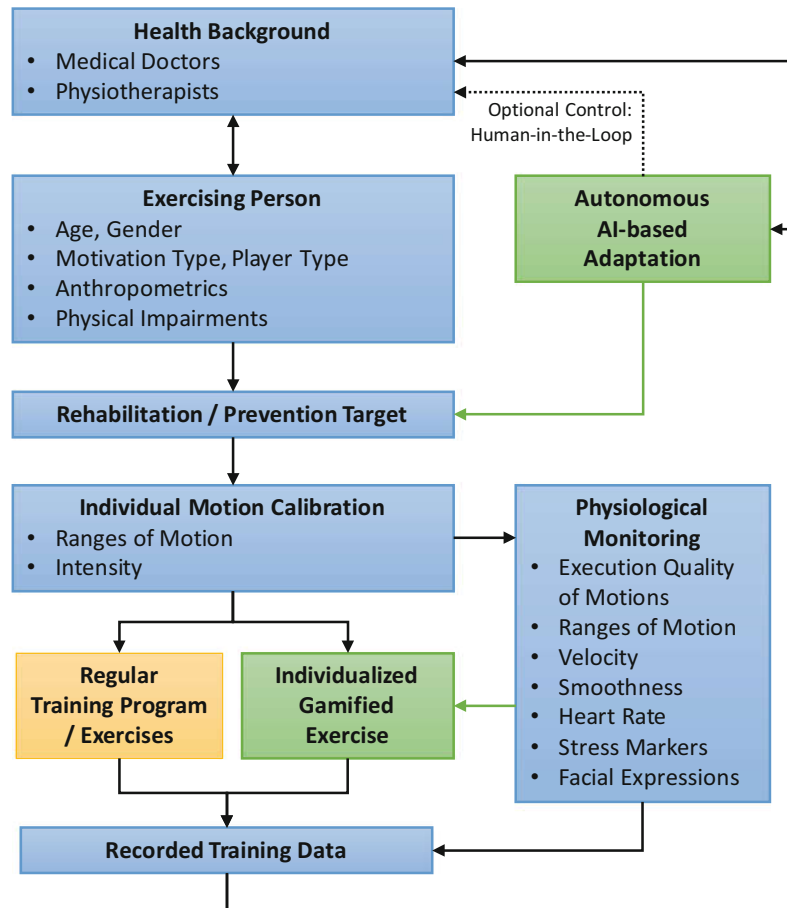
Building on such previous work, we propose a general framework that outlines the principal components of an autonomous, dynamic gamified system for smart rehabilitation and prevention training (Fig. 1).

Initially, such a system requires different levels of input from expert personal (Health Background). In due course, the continuous integration of expert input into the system (Recorded Training Data) allows the gradual replacement of human adjustments by the AI-based system. This system combines smart sensing with established evidence-based knowledge from guidelines or established intervention protocols for specific physical impairments (Physiological Monitoring). By using a gradual replacement strategy and a control mechanism (“Human-in-the-Loop”), the gamified training systems’ autonomy can gradually grow, following the expectable developments in wearable sensing and AI in the future.

The exercises are mainly chosen based on the physical impairment that needs to be treated or prevented. Further, the patient’s characteristics are considered (Exercising Person), including which type of gamification is best suited.

The exercise is monitored using smart sensing approaches. Depending on the type of exercise, different sensors can be applied: sensors worn on the body (i.e., IMUs in wristbands, belts, or implemented in smart apparel) or cameras can track the person’s motion [27]. Further, the concentration of specific metabolites (i.e., lactate) through an analysis of the produced sweat on the skin could be monitored and considered in evaluating the intensity of the exercise for the patient [28, 29]. An AI-supported analysis of facial expressions could further determine the subjective intensity.

Continuous motion monitoring during every training session can inform the exercise intensity’s adaption to the individual patient. As the proposed framework enriches rehabilitation or prevention training with gamification elements, such a continuous, near real-time observation (green arrow from Physiological Monitoring) will prevent overexertion. Improvements in the patient’s physical status can be detected, and the intensity can be gradually adjusted in both directions at an individual rate.



**Fig. 1.** The framework of an autonomous, dynamic gamified system for smart rehabilitation and prevention training. The schematic outlines the major components.

Adequate automated adaptation of the difficulty of training measures requires pattern analysis and pattern recognition beyond pure motion detection, i.e., collecting raw kinematic data and measuring the performance progression in detail concerning what is happening in the game. Thus, a specific game situation can justify an increased performance level in the short term without increasing the overall difficulty. For this purpose, a system of rules must be established, which might be best formalized via a classical element of AI, the decision tree. Such rule-based systems have also been established in the healthcare sector for some time as “rule-based decision support systems” or simply as medical decision aids.

In principle, experts (e.g., sports scientists in collaboration with physicians and computer scientists) can either develop decision trees or automatically induce them from data using machine learning techniques. There are several competing algorithms for the latter, particularly CHAIDs (Chi-square Automatic Interaction Detectors) and CARTs (Classification And Regression Trees). For example, motion sequences can be automatically annotated according to the criteria of freedom of movement, smoothness (“smoothness”), and compensation.

Intelligent adjustment of exercise goals is also critical to the treatment process when monitoring exercises. Musculoskeletal disorders are often the result of a complex interaction of extrinsic and intrinsic risk factors [30, 31], which must be considered when

adjusting exercise intensity. For example, adjusting the intensity should consider fatigue states and the resulting changes in movement mechanics. In summary, an intelligent or “smart” intensity adaptation of exercises is of critical importance for the success of autonomous, dynamic gamified systems for rehabilitation and prevention training.

Currently, the most promising solutions for such training in healthcare are probably so-called hybrid systems: systems combining rules from human experts with data-driven machine learning methods for movement analysis. One such model has recently been presented [32]. The superiority of hybrid systems is particularly eminent if, in addition to interventions based on movement patterns (for example, an indication that a knee flexion is too fast), game-specific interventions are generated. Thus, a rule adaptation in the game can automatically trigger a slower movement pattern. Another advantage of the hybrid approach is that it avoids the “black box of AI”, which is typical for machine learning or neural networks, as at least a part of the system remains explainable. This meets the widespread need for explainable AI (XAI). For the medical community, where unpleasant and lengthy measures are frequently required, the explainability of decisions to patients is particularly important [33] – as explainability is the basis for transparency and thus also for acceptance and trust.

### 3 Final Consideration

After introducing gamification and exergames, an overview of game-based approaches for movement monitoring, rehabilitation, and prevention training was provided. An increased risk of injury counters their proven effectiveness in increasing motivation since immersion in the gameplay can reduce pain stimuli’ perception or increase the risk of falling. This situation results in the need for dynamic difficulty adjustment in real-time at the patient level.

We presented a framework outlining the major components of such an autonomous, dynamic gamified system for smart rehabilitation and prevention training. In this framework, artificial intelligence methods based on sensor data from multiple inputs are suitable to monitor training even under complex conditions, including gamified approaches. Recent research suggests that hybrid approaches, which combine weighted results of expert-based systems with systems based on machine learning, are superior to purely human or purely machine approaches, especially in terms of flexibility. A further advantage is the explainability of at least the rule-based parts of such systems, which increases their acceptance in the medical domain.

### References

1. Wiemeyer, J.: Gesundheit auf dem Spiel?–Serious Games in Prävention und Rehabilitation. *Deutsche Zeitschrift für Sportmedizin*. **61**, 252–257 (2010)
2. Deterding, S., Sicart, M., Nacke, L., O’Hara, K., Dixon, D.: Gamification. using game-design elements in non-gaming contexts. In: CHI’11 Extended Abstracts on Human Factors in Computing Systems, pp. 2425–2428. Association for Computing Machinery, New York (2011). <https://doi.org/10.1145/1979742.1979575>

3. Ryan, R.M., Deci, E.L.: Intrinsic and extrinsic motivations: classic definitions and new directions. *Contemp. Educ. Psychol.* **25**, 54–67 (2000). <https://doi.org/10.1006/ceps.1999.1020>
4. Wulf, G., Chiviawosky, S., Cardozo, P.L.: Additive benefits of autonomy support and enhanced expectancies for motor learning. *Hum. Mov. Sci.* **37**, 12–20 (2014). <https://doi.org/10.1016/j.humov.2014.06.004>
5. Przybylski, A.K., Rigby, C.S., Ryan, R.M.: A motivational model of video game engagement. *Rev. Gen. Psychol.* **14**, 154–166 (2010). <https://doi.org/10.1037/a0019440>
6. Ryan, R.M., Rigby, C.S., Przybylski, A.: The motivational pull of video games: a self-determination theory approach. *Motiv. Emot.* **30**, 344–360 (2006). <https://doi.org/10.1007/s11031-006-9051-8>
7. Bartle, R.: Hearts, clubs, diamonds, spades: players who suit MUDs. (1996)
8. McNevin, N.H., Wulf, G., Carlson, C.: Effects of attentional focus, self-control, and dyad training on motor learning: implications for physical rehabilitation. *Phys. Ther.* **80**, 373–385 (2000). <https://doi.org/10.1093/ptj/80.4.373>
9. Bassett, S.F.: The assessment of patient adherence to physiotherapy rehabilitation. **31**, 8 (2003)
10. Ancillao, A., Tedesco, S., Barton, J., O’Flynn, B.: Indirect measurement of ground reaction forces and moments by means of wearable inertial sensors: a systematic review. *Sensors.* **18**, 2564 (2018). <https://doi.org/10.3390/s18082564>
11. Mundt, M., Koeppe, A., Bamer, F., David, S., Markert, B.: Artificial neural networks in motion analysis—applications of unsupervised and heuristic feature selection techniques. *Sensors.* **20**, 4581 (2020). <https://doi.org/10.3390/s20164581>
12. Wouda, F.J., et al.: Estimation of vertical ground reaction forces and sagittal knee kinematics during running using three inertial sensors. *Front. Physiol.* **9** (2018). <https://doi.org/10.3389/fphys.2018.00218>
13. Gerbrands, T.A., Pisters, M.F., Vanwanseele, B.: Individual selection of gait retraining strategies is essential to optimally reduce medial knee load during gait. *Clin. Biomech.* **29**, 828–834 (2014). <https://doi.org/10.1016/j.clinbiomech.2014.05.005>
14. Richards, R., van den Noort, J.C., Dekker, J., Harlaar, J.: Gait retraining with real-time biofeedback to reduce knee adduction moment: systematic review of effects and methods used. *Arch. Phys. Med. Rehabil.* **98**, 137–150 (2017). <https://doi.org/10.1016/j.apmr.2016.07.006>
15. Crowell, H.P., Davis, I.S.: Gait retraining to reduce lower extremity loading in runners. *Clin. Biomech.* **26**, 78–83 (2011). <https://doi.org/10.1016/j.clinbiomech.2010.09.003>
16. Napier, C., Cochrane, C.K., Taunton, J.E., Hunt, M.A.: Gait modifications to change lower extremity gait biomechanics in runners: a systematic review. *Br. J. Sports Med.* **49**, 1382–1388 (2015). <https://doi.org/10.1136/bjsports-2014-094393>
17. Noehren, B., Scholz, J., Davis, I.: The effect of real-time gait retraining on hip kinematics, pain and function in subjects with patellofemoral pain syndrome. *Br. J. Sports Med.* **45**, 691–696 (2011). <https://doi.org/10.1136/bjism.2009.069112>
18. Alcaide-Aguirre, R.E., Morgenroth, D.C., Ferris, D.P.: Motor control and learning with lower-limb myoelectric control in amputees. *JRRD.* **50**, 687 (2013). <https://doi.org/10.1682/JRRD.2012.06.0115>
19. Agresta, C., Brown, A.: Gait retraining for injured and healthy runners using augmented feedback: a systematic literature review. *J. Orthop. Sports Phys. Ther.* **45**, 576–584 (2015). <https://doi.org/10.2519/jospt.2015.5823>
20. Hooren, B.V., Goudsmit, J., Restrepo, J., Vos, S.: Real-time feedback by wearables in running: Current approaches, challenges and suggestions for improvements. *J. Sports Sci.* **38**, 214–230 (2020). <https://doi.org/10.1080/02640414.2019.1690960>
21. Sanno, M., Willwacher, S., Epro, G., Brüggemann, G.-P.: Positive work contribution shifts from distal to proximal joints during a prolonged run. *Med. Sci. Sports Exerc.* **50**, 2507–2517 (2018). <https://doi.org/10.1249/MSS.0000000000001707>

22. Sanno, M., Epro, G., Brüggemann, G.-P., Willwacher, S.: Running into Fatigue: The Effects of Footwear on Kinematics, Kinetics, and Energetics. *Med. Sci. Sports Exerc.* **53**(6), 1217–1227 (2021). <https://doi.org/10.1249/MSS.0000000000002576>
23. Willwacher, S., Sanno, M., Brüggemann, G.-P.: Fatigue matters: an intense 10 km run alters frontal and transverse plane joint kinematics in competitive and recreational adult runners. *Gait Posture* **76**, 277–283 (2020). <https://doi.org/10.1016/j.gaitpost.2019.11.016>
24. Hollander, K., Liebl, D., Meining, S., Mattes, K., Willwacher, S., Zech, A.: Adaptation of running biomechanics to repeated barefoot running: a randomized controlled study. *Am. J. Sports Med.* **47**, 1975–1983 (2019). <https://doi.org/10.1177/0363546519849920>
25. Korn, O., Tietz, S.: Strategies for playful design when gamifying rehabilitation: a study on user experience. In: *Proceedings of the 10th International Conference on Pervasive Technologies Related to Assistive Environments*, pp. 209–214. Association for Computing Machinery, New York (2017). <https://doi.org/10.1145/3056540.3056550>
26. Brach, M., Hauer, K., Rotter, L., Werres, C., Korn, O., Konrad, R., Göbel, S.: Modern principles of training in exergames for sedentary seniors: Requirements and approaches for sport and exercise sciences (2011). <https://doi.org/10.13140/RG.2.1.3762.2647>
27. Milosevic, B., Leardini, A., Farella, E.: Kinect and wearable inertial sensors for motor rehabilitation programs at home: state of the art and an experimental comparison. *Biomed. Eng. Online* **19**, 25 (2020). <https://doi.org/10.1186/s12938-020-00762-7>
28. Gao, W., Brooks, G.A., Klonoff, D.C.: Wearable physiological systems and technologies for metabolic monitoring. *J. Appl. Physiol.* **124**, 548–556 (2017). <https://doi.org/10.1152/jappphysiol.00407.2017>
29. Yokus, M.A., Songkakul, T., Pozdin, V.A., Bozkurt, A., Daniele, M.A.: Wearable multiplexed biosensor system toward continuous monitoring of metabolites. *Biosens. Bioelectron.* **153**, 112038 (2020). <https://doi.org/10.1016/j.bios.2020.112038>
30. Blagojevic, M., Jinks, C., Jeffery, A., Jordan, K.P.: Risk factors for onset of osteoarthritis of the knee in older adults: a systematic review and meta-analysis. *Osteoarthritis Cartilage* **18**, 24–33 (2010). <https://doi.org/10.1016/j.joca.2009.08.010>
31. Willwacher, S.: Running shoes: injury protection and performance enhancement. In: Müller, B. et al. (eds.) *Handbook of Human Motion*, pp. 1–16. Springer International Publishing, Cham (2017). [https://doi.org/10.1007/978-3-319-14418-4\\_121](https://doi.org/10.1007/978-3-319-14418-4_121)
32. Jung, H.-T., et al.: Rehabilitation games in real-world clinical settings: practices, challenges, and opportunities. *ACM Trans. Comput.-Hum. Interact.* **27**, 1–43 (2020). <https://doi.org/10.1145/3418197>
33. Holzinger, A., Biemann, C., Pattichis, C.S., Kell, D.B.: What do we need to build explainable AI systems for the medical domain? (2017). [arXiv:1712.09923](https://arxiv.org/abs/1712.09923) [cs, stat]