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REHABILITATION IN DIGITAL ENVIRONMENTS – BIOPHYSIOLOGICALLY MOTIVATED GAMIFICATION

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Abstract: *Nowadays, the process of cognitive or motor rehabilitation is mostly implemented in a traditional form. Paper-pencil cognitive exercises or physical exercises with instruments still dominate over digital environments. However, they require constant supervision by professionals, whose availability is relatively decreasing in an ageing society. Lack of supervision, in turn, results in a loss of motivation to exercise or, at the very least, ineffective, sometimes incorrect, exercise. In addition, traditional rehabilitation mechanisms are often repetitive and tedious. Sometimes a lack of supervision or routine results in a failure to adapt the challenges to the user's current needs.*

Digital environments and modern technology have much to offer in this regard. One aspect is gamification mechanisms, which work well in video games and allow players to be engaged for hours in challenges of modulated difficulty. Another aspect is the rapidly developing biosensors and tracking systems that allow the user's activity and biophysiological parameters to be monitored in real time. However, the combination of the benefits of technology and gamification stimulus mechanisms must be done in strict accordance with the user's capabilities in order to make the challenges constructive rather than destructive for the user's body and mental conditions. Ongoing monitoring of effort and mental workload and their synchronization with fatigue in the digital environment, supported by motivational gamification mechanisms, form the foundation of the correct and controlled exercises and rehabilitation.

Keywords: *rehabilitation, gamification, biofeedback, digital environment, human-technology.*

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Physical Activity

In the field of physical rehabilitation, a number of parameters can be monitored, and very different goals can be set. People with limited mobility aim to improve the range of movement of their limbs, or to better coordinate their movements, hence monitoring the current range of movement, or its trajectory/dynamics, can be an interface input parameter on which the achievement of goals depends. People with limited performance should perform movement exercises to improve it. Each age, for example, has its own recommended heart rate (ACSM 2000). If we treat the current heart rate as an input signal and make the task scenario dependent on it, this creates a fitness-dependent control mechanism. The analogy is with balance control.

Unfortunately, most of existing digital physical-rehabilitation games (exergames) effects and accompanying conditions of a series of exercises are usually assessed after the exercises (ex-post), resulting in bias (Furukado et al. 2021) and uncertainty of exercise. We are more often dealing with an analysis of the effects of exercise than with a monitored and personalized challenge (Ismail et al. 2022). Exergame interfaces are focused rather on threshold values or hardcoded patterns detection. An exergame gameplay balance correlated with physical challenges is rare and it should be kept in mind that very often the motivation to perform can arise from other circumstances (e.g. team competition, loss aversion, others) (Niforatos et al. 2021). It should also be taken into account that the actual strain on the body is usually different from the fatigue perceived by the individual (Stewart et al. 2022).

Exemplary, in Battussi et al (2007) level of difficulty is automatically adjusted if the system determines that the user should exert more or less physical effort maintaining users heart rate within its target zone. Masuko et al. (2006) proposed a boxing game in which the effort was adjusted so that the heart rate oscillated within the recommended range. Stach et al. (2009) proposed a game in which the heart rhythm was scaled so that people with different heart performance had comparable conditions to compete in a truck race controlled by a stationary bicycle. Hagen et al. (2016) recognized the problem of better balancing activity and rest in exergame exercises, but they solved this discreetly by varying the gameplay scenarios according to user fatigue. The problem is discussed at considerable depth in Martin-Niedecken's (2021) doctoral dissertation, only reinforcing the constant need for a conscious and tailored combination of physical exercise with a digital experience scenario.

Mental Workload

An important biophysiological aspect is Mental Workload (MWL). Cognitive load is a limited resource (Gomez 2021) hence the simultaneous processing of large amounts of information is also limited. When doing simple, undemanding work people tend to get bored, but when doing complex tasks MWL is high. A high MWL is not good for health and can impair memory, communication or activity, which is why injuries can occur in some professions (pilot, soldier, doctor). In this context, understanding how the human brain functions in everyday activities and tasks is the basis of neuroergonomics (Parasuraman 2011). Tasks should be stimulating and not overloading.

While classical approaches to MWL monitoring include sets of questions i.e. NASA TLX (Hart et al. 1988) or SWAT (Reid et al. 1988), this approach is biased as it is performed after the task/activity has been completed. At the same time, modern technology allows MWL to be monitored in real time by analyzing biophysiological signals. Among these, Electroencephalogram (EEG), Galvanic Skin Response (GSR), Heart Rate Variability (HRV), Electrocardiogram (ECG) or even temperature are descriptive when it comes to MWL. Among the above, the EEG signal seems to be one of the most interesting, as its information capacity is higher than the other bio signals (Kakkos et al 2021). The numerous scientific papers (Mahesh et al. 2021, Zammouri et al. 2018) that detect MWL from the EEG signal with high efficiency should be a direct guide for designers of exergames monitoring cognitive load.

Biophysically Motivated Gamification

Despite a number of attempts to make bio-physiological signals a control mechanism to influence task performance in digital environments, they do not allow psycho-physical parameters to be controlled to the recommended range. It is easy to find solutions that use gameplay as a cover for physical exercise (Hagen 2016), but they mostly implement this unreflectively (Martin-Niedecken 2021). Although Ketelhut et al (2022) draws attention to the conscious use of heart rate in the design of physically based games (exergames), it is difficult to find work that addresses MWL or other physiological signal modalities.

Finally, however, it should be noted that professional and automatic exercise management requires medical expertise and this cannot always be codified in a computer program. While artificial intelligence techniques support the creation of recommendation systems quite strongly, it is worth mentioning that the monitoring or visualization of key biophysiological parameters alone is as obtainable as it is possible to couple with an interactive digital simulation scenario in many rehabilitation scenarios.

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