CHAPTER I

INTRODUCTION

1.1 Introduction

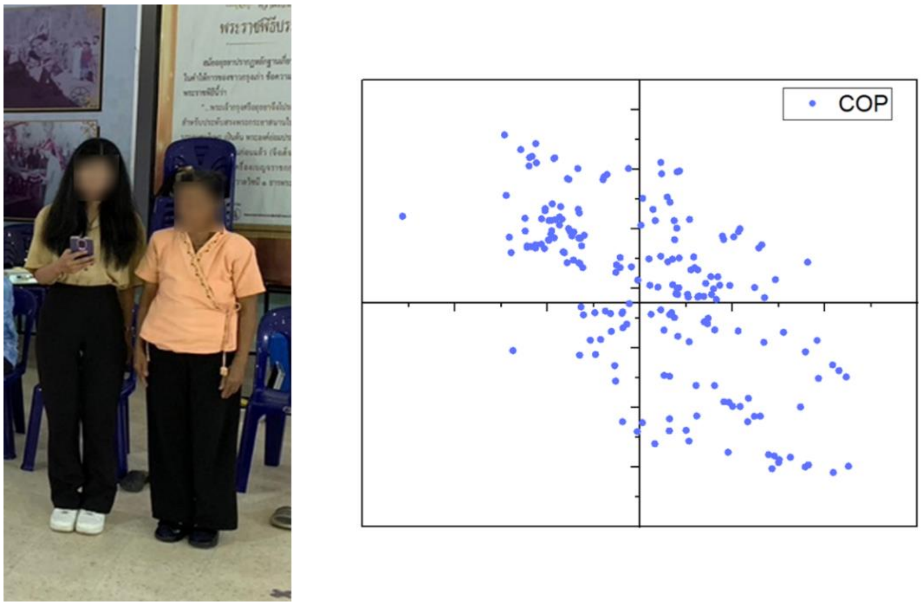
Falls are a common issue among the elderly, individuals with decreased independence, and those with physical limitations (Danielsen et al., 2016). The global population aged 65 and older is projected to exceed 1.5 billion by 2050, making the risks and complications associated with falls a significant concern (United Nations, 2020). Falls can result in severe injuries, increased activity limitations, heightened fear of falling, depression, and a reduced quality of life. Additionally, medical costs related to falls are substantial, estimated at around $50 billion in 2015 (Florence et al., 2018).

Studies have shown that physical therapy can improve balance, prevent falls, and enhance independence among the elderly (Thomas et al., 2010). Physical therapy is, therefore, an effective intervention to help older adults regain lost abilities and return to independent living. However, traditional rehabilitation activities are often repetitive, leading to boredom and a lack of motivation among patients to engage in physical therapy (Teruel et al., 2019).

Previous research has found that patients who enjoy rehabilitation activities are more likely to spend time on them (Hocine and Gouaich, 2011). This suggests that designing rehabilitation activities in the form of games has the potential to enhance the rehabilitation process by creating an engaging environment that motivates patients (Sekhavat, 2017). Serious games (SG) have been specifically designed for rehabilitation purposes and are widely used due to their ability to attract players and effectively support the rehabilitation process (Maheu-Cadotte et al., 2021).

The difficulty level of rehabilitation games can usually be typically determined by therapists based on the initial statistical profile of the player, or by the scores derived from the in-game achievements at the end of the game. However, data collected from the player's physical condition during the game play may provide insights to the balance impairments of the player. Such data input for SG can be obtained from sensor devices, such as force pressure plates (Riedmann, 2022; Baranyi, 2013), wearable sensor devices (Agrawal et al., 2023) or virtual reality (VR) (Mariselvam et al., 2023) hardware systems. While VR systems provide immersive experiences, the costs and system effort-demanding set up may pose challenges to implement. On the other hand, force pressure plates may be less costly, however, the static set up may limit the dynamics of players' movements. On the other hand, wearable sensors, such as wireless pressure sensors embedded in insoles (Agrawal et al., 2023), can offer a more natural degree of freedom for movements and enable insights of dynamics of the player's balance impairment (Agrawal et al., 2023).

Furthermore, pressure sensors from force plates or wireless insoles can provide insights to the Center of pressure (COP) of the player. The COP is the point where all forces act on a surface, resulting from the combination of forces exerted by the body on the ground. The COP plays a critical role in maintaining balance and preventing falls during standing or walking. Furthermore, COP serves as an indicator of pressure distribution on the surface and is commonly used in the analysis of balance and movement. Measuring COP helps enhance walking efficiency, reduce the risk of fall-related injuries, and promote greater stability and safety in walking (Physiopedia, 2023). The measurement of COP is conducted while the participants stand upright on a pressure sensor. The device records the pressure exerted on the surface in all directions. This data is used to analyze balance and body stability.



(a) (b)

Figure 1.1.1 **(a)** Illustration of the data acquisition of center of pressure using pressure-sensing insoles as the measurement device **(b)** Sample of COP while standing

In (Riedmann, 2022), the Nintendo Wii Balance Board (WBB) is a widely used low-cost force plate to measure the COP of the player to feed as input to a SG for balance impairment treatment. In particular, the CoP data was used to adjust the difficulty according to the player’s balance ability and enhance the player’s experience in a personalized manner. To evaluate the player’s balance ability, a heuristic method was used with baseline data from healthy players. The difficulty of each game level has been based on the physiotherapists requirements. However, the game dynamically adjusts the game level difficulty based on the user performance. Since level generation is parameterized by patient balance scores, it relies on the patient’s balance score obtained from the heuristic algorithm to quantify the patient’s balance ability, to yield meaningful results. The heuristic model is a problem-solving approach that emphasizes speed by using predefined rules or principles to find a "good enough" solution in situations where achieving a precise answer would require excessive resources. Although it does not guarantee the best possible outcome, heuristics can provide suitable solutions within a limited timeframe (Beheshti and Shamsuddin, 2013).

Figure 1.1.2 Nintendo Wii Balance Board (WBB) (Nintendo., 2025)

In (Riedmann, 2022), the proposed SG called Walk in the Park is an extension of a previous rehabilitation SG called RehabLabyrinth (Baranyi et al., 2013). While RehabLabyrinth utilized static game levels that require manual selection by therapists or physicians, Walk in the Park introduced automatic adaptive game levels. These adaptive levels are designed to boost patient motivation and facilitate intensive and repetitive exercises, making them more effective compared to the original SG.

Recently, the concept of Reinforcement learning (RL), a branch of artificial intelligence, has been introduced to promote rehabilitation and engagment. RL learns through trial-and-error interactions with its environment, receiving feedback to refine decision-making strategies over time. This ability sets RL apart from traditional Machine learning, which focuses on processing pre-existing datasets. RL, on the other hand, can adapt and evolve continuously based on real-world scenarios (Jayaraman et al., 2024).

RL has been applied in various fields, including healthcare, due to its ability to adapt and learn from complex environments. Its capacity to learn continuously from data can significantly improve clinical trial outcomes and healthcare strategies (Jayaraman et al., 2024). For instance, research on personalized chemotherapy dosing (Zhao et al., 2009; Ahn and Park, 2011; Ebrahimi Zade et al., 2020) utilizes RL to optimize the amount of chemotherapy tailored to individual patients. Another example is stroke rehabilitation, where RL is used with robotic arms equipped with two-degrees-of-freedom (DoFs) to facilitate arm rehabilitation. These robots monitor exercise methods to enhance therapeutic efficiency and ensure patient safety during exercise. This approach not only increases patient engagement but also accelerates the rehabilitation process effectively (Choutri et al., 2023).

In the context of balance rehabilitation, RL has been proposed to adjust game difficulty based on patients' skills and abilities. RL can significantly enhance the effectiveness of SG for physical rehabilitation for patients by providing personalized and adaptive training experiences (Hornak et al., 2019). This ensures maximum efficiency in the rehabilitation process through dynamic difficulty adjustment. Specifically, RL algorithms can dynamically modify the difficulty level of tasks based on the patient’s performance. If the patient performs well, the game increases the challenge to promote progress conversely, if the patient struggles, the game reduces the difficulty to lower barriers. RL can also generate personalized feedback for each patient, focusing on areas requiring improvement. This capability further enhances the efficiency of the rehabilitation process (de Oliveira Andrade et al., 2014).

In this thesis, we therefore develop a game level difficulty adjustment method customized for each user based on RL using the user’s COP directly obtained during the game. The SG is based on the SuraSole maze game (Suratec, 2024), which is designed by physiotherapists for balance impairment treatment. The SuraSole maze game is based on the patient’s COP obtained from SuraSole wearable wireless pressure insoles to gather real-time patient movements, instead of a static balance board as in (Riedmann, 2022; Baranyi, 2013). The patient’s sensor COP data is fed into the RL algorithm, which then updates the game environment and tasks based on this information. In particular, the RL technique called Q-learning (see Appendix B), is used to learn policies that determine the best actions (game level) to maximize patient progress. Table 1.1.1 compares the features of the SGs referred to in this research work. The objectives and contributions of this thesis proposal are as follows.

	RehaLabyrinth [10]	Walk in the park [9]	Surasole Maze	This_Thesis
Gamification elements	✓	✓	✓	✓
COP Calibration	✓	✓	✓	✓
Balance evaluation	X	✓	X	✓
Performance feedback	✓	✓	✓	✓
Difficulty adaptation	X	✓	X	✓
Method of difficulty adaptation	X	Heuristics	X	Reinforcement learning
Equipment				

Table 1.1.1 Comparison of core aspects in this research

1.2 Objectives

1.2.1 To develop a serious game based on reinforcement learning that can adjust to the participant's Center of pressure (COP) to suggest balance training game levels for each player.

1.2.2 To test the proposed game on healthy subjects to assess their COP, gait parameters, engagement, and safety of the serious game.

1.3 Contributions

1.3.1 Development of a prototype SG for balance impairment rehabilitation, designed as a future framework that utilizes adaptive difficulty adjustment within the game based on patients' abilities, leveraging reinforcement learning to support effective balance recovery tailored to individual needs.

1.3.2 Use of COP collected in during the serious game from the wireless pressure sensor insoles.

1.4 Scope of research

1.4.1 Develop a game difficulty adjustment system for balance rehabilitation using Reinforcement learning with simulation and data collected from wireless pressure sensor insoles (SuraSole).

1.4.2 Test the game on healthy participants to evaluate balance, safety, and engagement in gameplay.

1.4.3 Develop computational processes and analysis methods for Center of Pressure (COP) data to adjust the game levels to suit individual players.

1.5 Hypotheses

1.5.1 Using Reinforcement learning for game difficulty adjustment can improve players' balance.

1.5.2 COP data collected from wireless pressure sensor insoles can be effectively processed to adjust game difficulty based on players' abilities.

1.5.3 Players will be more engaged and find the game enjoyable when difficulty levels are dynamically adjusted according to their skills.

1.6 Expected Benefits

1.6.1 A new tool for balance rehabilitation that adapts game difficulty based on players' COP.

1.6.2 Increased motivation and enjoyment for individuals undergoing balance rehabilitation through gamified activities.

1.6.3 Reduced risk of fall-related injuries for elderly individuals or those with balance impairments.

1.6.4 Support for rehabilitation processes using modern technology that dynamically adapts based on real-time player data.