CHAPTER II
LITERATURE REVIEW

2.1 Introduction

The development of games for balance rehabilitation has gained increasing attention in recent years due to their potential to enhance the effectiveness of therapy and motivate patients. Previous research has developed various approaches to integrate gaming technology into rehabilitation processes to improve balance and movement. One of the widely recognized techniques is the application of Reinforcement learning (RL), which can enhance the effectiveness of Serious games (SG) for physical rehabilitation (Hornak et al., 2019). RL's ability to automatically adjust difficulty levels ensures that each training session is tailored to the patient's ability (Sekhavat, 2012; Mariselvam et al., 2023; Khabbaz et al., 2023).

In the context of balance rehabilitation, related studies emphasize the importance of gaming technology that can dynamically adapt to the unique characteristics of individual players. This study adopts these concepts to develop the SuraSole maze game, which uses RL to adjust game difficulty levels based on Center of pressure (COP) data measured from SuraSole insoles. The goal is to support effective balance rehabilitation while evaluating the game's impact on motivation and balance control capabilities among diverse target groups.

This chapter is divided into three main sections:

1) Technology of SuraSole Insoles and SuraSole maze game: Section 2.2-2.3 focus on the structure and functionality of SuraSole and the mechanisms of the SuraSole maze game.

2) Concept of RL: Section 2.4 explains the principles of RL and how it is applied in rehabilitation games.
3) Calculation of balance parameters: Section 2.5 describes methods for measuring and analyzing various parameters related to balance assessme.

2.2 SuraSole

SuraSole is a smart insole based on wearable sensor technology and the Internet of Things. The SuraSole sole is designed to help doctors, physical therapists and patients by providing home-based rehabilitation walking and balance impairment physical therapy, which can monitor the development of physical therapy without having to come to the hospital. This helps save the cost of imported equipment and travel and face-to-face treatment time for physiotherapy at the hospital. SuraSole enables balance training information by transmitting information via mobile phones or computer to the hospital or doctors and physiotherapists.

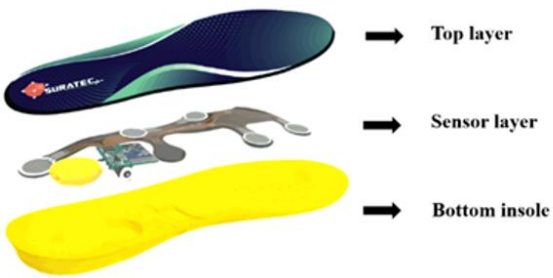

Figure 2.2.1 SuraSole smart insole

The insole system utilized in this study was embedded with multiple Force Sensitive Resistor (FSR) 8 sensors, each measuring 18 mm in diameter, integrated within both insoles. These sensors were strategically positioned to monitor variations in pressure. The collected data were segmented into five distinct zones: the hallux (HA1), fourth toe (HA2), medial forefoot (M1), central forefoot (M3), lateral forefoot (M5), midfoot (MF), lateral foot (LF) and heel (HF). The FSR sensors were connected to a microcontroller through a voltage divider configuration, with the output processed by a 10-bit Analog-to-Digital Converter (ADC). The system was calibrated to measure forces within a range of 0 to 196.2 N (0 to 20 kg), ensuring a response time of less than 10 microseconds. The sensors operated at a sampling frequency of 20 Hz, transmitting real-time data via Bluetooth to a smartphone, where the information was subsequently uploaded to a database server for analysis.

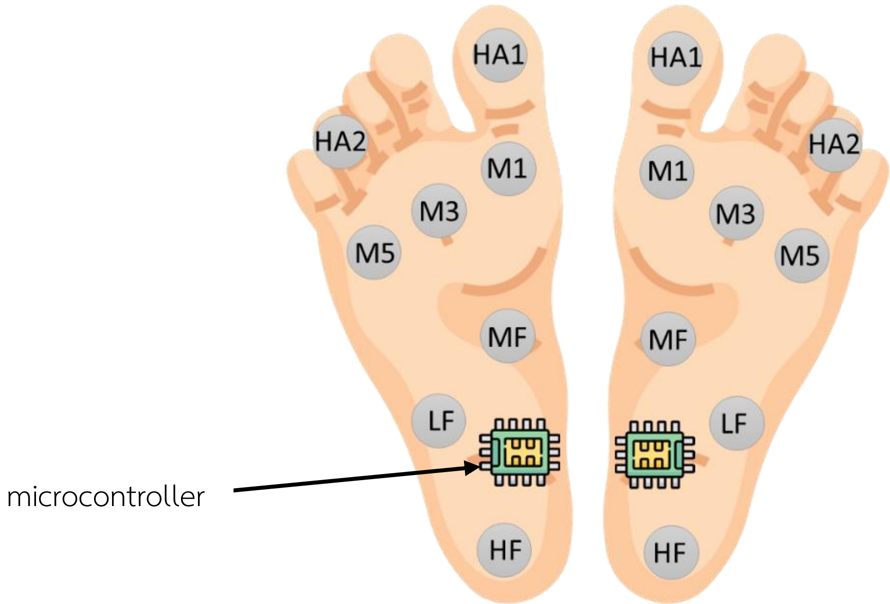

Figure 2.2.2 Sensor points distributed across specific foot zones

2.3 SuraSole maze game

The SuraSole maze game is a rehabilitation and physical therapy SG gaming application that helps patients improve their balance and weight transfer abilities (Suratec, 2024). Developed by physiotherapists, the game show in figure 2.3.1 (a)–(g) offers an engaging experience and tracks progress through scoring, fostering motivation and user satisfaction. The objective of the game is to navigate a ball through a maze, shown in Figure 2.3.1 (f), created from obstacles to reach the finish line. Additionally, players must collect bonus points to score. Each level is timed, with the clock starting when the player moves and stopping when they reach the finish line. Once the player reaches the finish line, the game concludes.

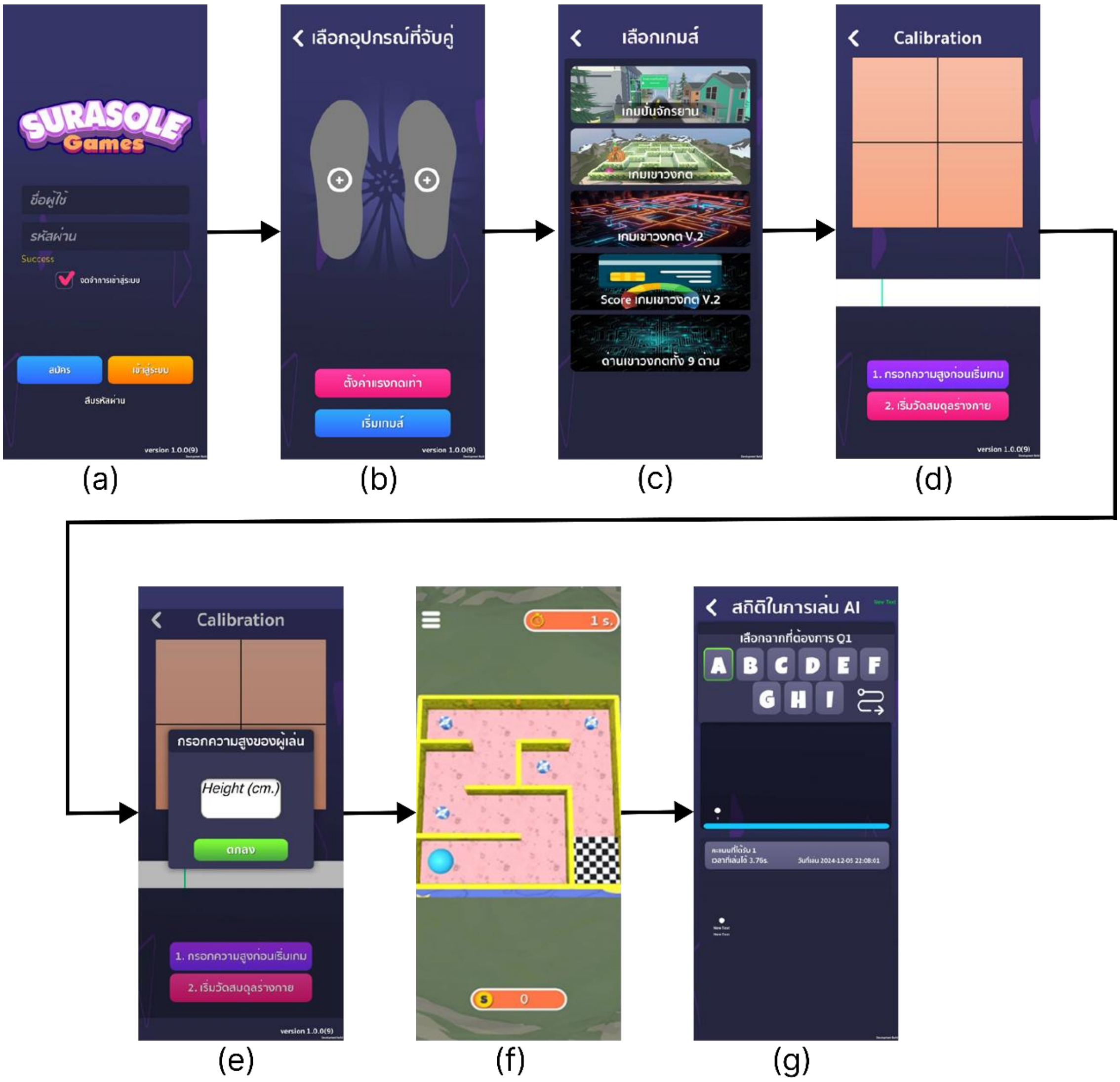

Figure 2.3.1 SuraSole maze game

In the process of balance rehabilitation, patients often attempt to compensate for their weakest points of COP by shifting more weight to the stronger side that is unaffected. Such actions can negatively impact the outcomes of rehabilitation. Physical therapists can observe these compensatory efforts and provide guidance for improvement. Game level design should require patients to shift their weight towards their weaker side, promoting more effective rehabilitation outcomes (Riedmann, 2022).

This thesis therefore develops a RL model that adjusts the game level difficulty in which the path of the ball is chosen to reach the game's goal, by focusing on path selection that can shift weight towards the player's weakest direction of the COP to help the ball reach the finish line. The primary outcome is to achieve improvement in balance in terms of COP. The secondary outcome is to stimulate internal motivation and encourage full participation in the health rehabilitation and physical therapy process, aiming to improve rehabilitation outcomes. For more details on mapping the SuraSole maze game to the RL framework, see Chapter 3.

2.4 Reinforcement learning algorithm

Reinforcement learning (RL) represents a distinct category within machine learning algorithms, primarily operating on datasets characterized by their uncertainty and complexity. In this framework, RL agents are rewarded for making correct decisions and penalized for incorrect ones. The core objective is to maximize the cumulative reward, effectively treating each problem as if it were a game. This unique approach allows the model to adapt and learn new skills over time, making RL particularly suited for applications such as AI gaming, robotic navigation, and any other application requiring the acquisition of new and complex abilities. Through this process, RL aims to continually improve its decision-making capabilities, thereby enhancing its performance in the designated tasks. For more details on RL, see Appendix A.

2.5 Literature of RL for difficulty adjustment in rehabilitation games

RL plays a crucial role in healthcare and physical therapy, particularly in the development of SG that aim at dynamically adjusting game difficulty levels to optimally challenge each player (Jayaraman et al., 2025; Seyderhelm and Blackmore, 2021). Moreover, RL enhances player immersion in therapy by making the game more engaging as difficulty is adjusted according to their skills, thereby motivating and increasing participation in the physical rehabilitation process.

A significant difference between RL and traditional control systems is that, while control systems depend on theoretical models, RL is driven by outcomes. This enhances the efficiency of treatment methods to suit individual needs by evaluating and comparing different approaches within a specific personal context. For instance, RL facilitates the selection of the most effective treatment strategy for an individual by weighing all possible options for that person, thereby personalizing the rehabilitation or healthcare process with precision that adapts to the changing ability levels of the player.

RL also reduces the burden on medical professionals in monitoring and adjusting treatment programs by utilizing automated systems that can adapt treatments appropriately in real-time. Moreover, RL enhances the user experience through various rehabilitation games or programs, making the process more engaging and motivating for patients to actively participate in their rehabilitation. RL not only adjusts the difficulty level of rehabilitation to suit individual needs but also increases the likelihood of long-term success in the rehabilitation process (Jayaraman et al., 2024).

In (Sekhavat, 2017), a rehabilitation system was introduced that automatically adjusts the difficulty level of games based on patients' skills using the RL technique. This system was specifically designed to enhance motor recovery, particularly in stroke patients. The game utilized in this study involved players controlling a character through a Kinect motion sensor, which could capture body positions and movements. Players were required to raise their arms to strike illuminated balls along a curved line. The system dynamically adjusted parameters such as the character's speed, ball size, and the distance between curves to match the players' abilities. In the RL process, the system used metrics like the difference between wins and losses and scores from each round as indicators of the state. Actions included adjusting the character's speed, ball size, and the distance between curves to tailor the game's difficulty to the players' skills. Rewards were designed to encourage continuous gameplay and skill development, such as reducing score differences and increasing opportunities for progression in each round. The results of this system demonstrated that MPRL was effective in both enhancing player satisfaction and promoting long-term motor control recovery.

In (Khabbaz et al., 2023), the SmartBird game was developed to enhance communication skills in children with Autism Spectrum Disorder (ASD). The game integrates RL with Fuzzy logic to dynamically adjust the game difficulty according to the player’s skills. Players control a bird in the game to avoid obstacles, escape eagles, and dodge hunters' projectiles. The objective of the game is to improve the gameplay ability and communication skills of children with ASD. In the RL process, the game's state is defined by the player’s skill level, measured using a factor called the Skill Factor, which reflects the ability to avoid obstacles and enemies in the game. Rewards are determined by the reduction in the character’s in-game health, and the system utilizes the RL to learn how to select actions, such as increasing or decreasing the number of obstacles or enemies, to match the player’s skill level. The goal is to balance the challenge and enjoyment of the game while promoting long-term communication skill development. Experimental results from a sample group of 15 children with ASD showed that the game significantly improved their communication skills and gameplay abilities. The game’s adaptive design particularly contributed to maintaining the children’s engagement and supporting their continuous skill development during gameplay.

In (Mariselvam et al., 2023), developed a virtual reality (VR) rehabilitation game utilizing RL to support children with Down syndrome, particularly those reliant on wheelchairs. The game was designed to enhance both physical and cognitive skills, such as muscle control, hand-eye coordination, and social interaction. Players used a VR headset and controllers to play a game focused on controlling a ball on a board to score points. In the RL process, the system analyzed the player’s abilities and used states (e.g., hand movements, responses to actions, and ball positions) as key indicators. Rewards were given when players successfully moved the ball to the desired position, while actions (e.g., adjusting the board’s tilt or the ball's movement) were determined to help players develop missing skills. The primary goal of the system was to build confidence and physical control in children while providing an enjoyable and skill-appropriate experience. Experimental results demonstrated that RL significantly improved players’ performance and scores. Additionally, the game showed potential for long-term development in children with Down Syndrome. However, further system training is required to substitute human caregivers in certain scenarios.

From the review of related research, it was found that studies applying SG for balance rehabilitation using RL remain limited, reflecting opportunities for further development in this area. In particular, there is potential to advance the dynamic adjustment of game difficulty to suit a diverse range of target patients. It is anticipated that this effort will lead to the creation of new approaches that can be effectively applied in rehabilitation processes.

2.6 Balance ability assessment

The Balance score is a measure used to assess an individual's balance ability. In the context of balance rehabilitation, the Balance score serves as a crucial parameter for evaluating the effectiveness of rehabilitation processes by comparing scores before and after the intervention (Riedmann, 2022). In this study, the Balance score is utilized to analyze the impact of the developed SuraSole maze game. It involves calculating various parameters to evaluate improvements in the participants' balance ability, both quantitatively and qualitatively. Additionally, it acts as a key indicator for refining the game to effectively meet the needs of diverse target groups.

We used a Balance score, ranging from 0 to 100, to assess balance ability during weight-shifting exercises. This score allows for the measurement of efficiency and progress in balance rehabilitation and provides important information about the participants' balance deficits. The relevant parameters include COP velocity, RMS amplitude in the anterior-posterior and lateral directions, and RMS velocity in the anterior-posterior and lateral directions.

The calculation of the COP from SuraSole sensor data involves two main directions COP in the mediolateral direction (ML or COP_x) and COP in the anterior-posterior direction (AP or COP_y). The calculation can be performed as follows,

$$COP_x = \frac{\sum_{i=1}^{8}(F_{Li} \times X_{Li}) + \sum_{i=1}^{8}(F_{Ri} \times X_{Ri})}{\sum_{i=1}^{8}(F_{Li} + F_{Ri})} \quad (2.1)$$

$$COP_y = \frac{\sum_{i=1}^{8}(F_{Li} \times Y_{Li}) + \sum_{i=1}^{8}(F_{Ri} \times Y_{Ri})}{\sum_{i=1}^{8}(F_{Li} + F_{Ri})} \quad (2.2)$$

where

F_{Li} and F_{Ri} are the force measured by the i-th sensor on the left foot and right foot,

X_{Li} and X_{Ri} are the position in the X-axis of the i-th sensor on the left foot and right foot,

Y_{Li} and Y_{Ri} are the position in the Y-axis of the i-th sensor on the left foot and right foot.

Sway path refers to the area traversed by the COP over a specific period, serving as an indicator of postural control capability. An increase in the Sway path area may reflect a decrease in balance-maintaining ability. However, the value can also be high in cases where the body exhibits good balance or low in cases of unstable posture, which might not always correspond to the actual ability to control balance (Palmieri et al., 2002).

The Sway path can be analyzed separately in the mediolateral direction (ML_sway), representing lateral movements, and in the anterior-posterior direction (AP_sway), representing forward and backward movements. These can be calculated using equations 2.3 and 2.4, respectively,

$$\text{ML\_sway} = \sqrt{\frac{1}{N} * \sum_{i=1}^{N} (\Delta COP_x[i])^2} \tag{2.3}$$

$$\text{AP\_sway} = \sqrt{\frac{1}{N} * \sum_{i=1}^{N} (\Delta COP_y[i])^2} \tag{2.4}$$

where

N is the number of COP measurements in the experiment,

$\Delta COP_x[i]$ is change in COP values along the X-axis between the i-th data point and the previous point $i-1$ calculated as $COP_x[i] - COP_x[i-1]$,

$\Delta COP_y[i]$ is change in COP values along the Y-axis between the i-th data point and the previous point $i-1$ calculated as $COP_y[i] - COP_y[i-1]$.

COP velocity refers to the rate of change of the position of the center of pressure (COP) over time. An increase in COP velocity indicates a decline in postural control, while a decrease in COP velocity suggests a reduction in the ability to maintain posture (Palmieri et al., 2002). The COP velocity can be calculated from,

$$COP\ velocity = \frac{\frac{1}{N}\sum_{i=1}^{N}\sqrt{(\Delta COP_x[i])^2 + (\Delta COP_y[i])^2}}{Duration} \tag{2.5}$$

where

N is the number of COP measurements in the experiment,

$\Delta COP_x[i]$ is change in COP values along the X-axis between the i-th data point and the previous point i-1,

$\Delta COP_y[i]$ is change in COP values along the Y-axis between the i-th data point and the previous point i-1,

$Duration$ is total time span of the COP measurement.

RMS amplitude measures the average absolute displacement around the mean COP. A decrease in RMS amplitude is associated with an improvement in the ability to maintain an upright posture, whereas an increase in RMS amplitude indicates a decline in postural control (Palmieri et al., 2002). The parameter can be determined by

$$RMS_{amp\_x} = \sqrt{\frac{1}{N} * \sum_{i=1}^{N}(x_i - \mu_x)^2} \quad (2.6)$$

$$RMS_{amp\_y} = \sqrt{\frac{1}{N} * \sum_{i=1}^{N}(y_i - \mu_y)^2} \quad (2.7)$$

where

N is the number of COP measurements in the experiment,

x_i and y_i are the data points of COP_x and COP_y respectively,

μ_x and μ_y are the mean values of COP_x and COP_y respectively.

RMS velocity refers to the change in velocity over a certain period. It is a measure that reflects the fluctuations or variations in velocity. 'An increase in RMS velocity corresponds to an increase in COP displacement, which indicates hurried or uncontrolled weight distribution during the experiment' (Palmieri et al., 2002). The RMS velocity in x and y directions are defined as

$$RMS_{vel\_x} = \sqrt{\frac{1}{N-1} * \sum_{i=1}^{N}(\Delta x_i - \mu_{\Delta x})^2} \quad (2.8)$$

$$RMS_{vel\_y} = \sqrt{\frac{1}{N-1} * \sum_{i=1}^{N}(\Delta y_i - \mu_{\Delta y})^2} \quad (2.9)$$

where

N is the number of COP measurements in the experiment,

Δx_i and Δy_i are the changes at each point of COP_x and COP_y respectively,

$\mu\Delta x$ and $\mu\Delta y$ are the mean values of the changes in COP_x and COP_y respectively.

Typically, the Balance scores are compared before and after gameplay among the participants. This parameter highlights the effectiveness of the game in improving balance. Additionally, this comparison can be used to further analyze factors influencing rehabilitation outcomes.

After obtaining the individual balance parameters, we calculated the overall Balance score as described in (Riedmann, 2022), which reflects the relationship between various attributes to assess balance ability during gameplay. This score has a maximum value of 100, with the score decreasing as the deviation from the baseline distribution increases. The greater the deviation from the baseline distribution, the lower the balance ability score. The Balance score can be determined from

$$BS = \max\left(0, 1 - \frac{Mah(x)}{LST}\right) * 100 \tag{2.11}$$

where $Mah(x)$ represents the Mahalanobis distance of the new observation x which can be calculated from

$$Mah(x) = \sqrt{(x - \mu)^T \Sigma^{-1} (x - \mu)} \tag{2.12}$$

where

x is the data vector of the participant (e.g., COP velocity, RMS amplitude, and RMS velocity),

μ is the mean data vector of normal individuals (e.g., COP velocity, RMS amplitude, and RMS velocity),

$\sum^{-1}$ is the covariance matrix,

T denotes the transpose of the vector.

The LST is the Lower Scoring Threshold for the Balance score, allowing participants with deviations from the typical distribution but with notable changes to increase their overall score, which can be calculated from

$$LST = \mu_{Mah} + 5 * \sigma_{Mah} \tag{2.13}$$

where

μ_{Mah} is the mean of the Mahalanobis distance for the entire sample group,

σ_{Mah} is the standard deviation of the Mahalanobis distance for the entire sample group.

2.7 Summary

Chapter 2 presents the backgroud on technology, theoretical principles, and methodologies related to the development of the SuraSole maze game. It emphasized the use of the SuraSole smart insoles for collecting balance data, the application of RL for dynamic game difficulty adjustment, and the analysis of balance parameters crucial for rehabilitation. All this information provides a foundation for the development and evaluation of the balance rehabilitation game.