

**FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO**

# **Development of an Adaptive Serious Gaming Platform for Upper Limb Stroke Rehabilitation**

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**Master's Dissertation in Bioengineering, Specialization in Biomedical Engineering**

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July 27, 2026





# Resumo

O acidente vascular cerebral constitui uma das principais causas de incapacidade a longo prazo em todo o mundo, sendo a reabilitação do membro superior essencial para promover a recuperação funcional e melhorar a qualidade de vida dos sobreviventes. Contudo, os métodos convencionais de reabilitação são frequentemente limitados pela escassez de recursos clínicos, pela reduzida intensidade terapêutica e pela dificuldade em manter a motivação e a adesão dos doentes ao tratamento durante períodos prolongados. Neste contexto, os jogos sérios e as tecnologias de captura de movimento têm emergido como abordagens promissoras para proporcionar um treino intensivo, personalizado e motivador. Apesar dos avanços registados no desenvolvimento de jogos sérios, na captura de movimento, na reabilitação adaptativa e no suporte à reabilitação domiciliar, muitas das soluções existentes apresentam ainda limitações ao nível da personalização, da avaliação abrangente da qualidade do movimento e da integração entre a supervisão do terapeuta e os mecanismos adaptativos de reabilitação.

Esta dissertação apresenta o desenvolvimento, a implementação e a avaliação preliminar de uma plataforma de jogos sérios baseada no Kinect para a reabilitação do membro superior após acidente vascular cerebral. A plataforma proposta integra quatro jogos de reabilitação direcionados para diferentes funções motoras, assentes numa arquitetura de reabilitação em ciclo fechado, que combina avaliação do movimento em tempo real, regulação adaptativa da dificuldade, deteção de movimentos compensatórios, feedback multimodal e gestão da reabilitação orientada pelo terapeuta. A calibração específica para cada doente é utilizada para personalizar o espaço de reabilitação, enquanto indicadores computacionais da qualidade do movimento, inspirados na Fugl-Meyer Assessment for Upper Extremity (FMA-UE) e no Wolf Motor Function Test (WMFT), permitem uma avaliação objetiva e contínua do desempenho durante a realização dos jogos. Adicionalmente, foi desenvolvida uma interface dedicada ao terapeuta, que suporta a configuração dos exercícios, a monitorização dos doentes e a personalização dos protocolos de reabilitação.

A plataforma foi avaliada através de um estudo preliminar de viabilidade com 9 participantes saudáveis, com idades compreendidas entre os 19 e os 87 anos, com o objetivo de avaliar a sua usabilidade, funcionalidade, aceitação pelos utilizadores, motivação, variedade dos jogos, clareza das instruções, dificuldade dos exercícios e utilidade percebida para a reabilitação, antes da sua validação clínica. Os participantes realizaram sessões de reabilitação, seguidas de uma avaliação quantitativa e qualitativa, recorrendo a questionários baseados em escalas de Likert e a comentários abertos. Os resultados evidenciaram uma receção globalmente positiva, com classificações elevadas em todas as dimensões avaliadas, indicando que a plataforma proporciona uma experiência de reabilitação intuitiva, motivadora e bem aceite. O estudo permitiu igualmente identificar limitações técnicas, nomeadamente relacionadas com a personalização do espaço de trabalho, a deteção da postura e as restrições inerentes ao sensor Kinect, fornecendo orientações concretas para futuras melhorias do sistema.

Embora não tenha sido avaliada a eficácia clínica, este trabalho demonstra a viabilidade técnica da integração de jogos sérios, captura de movimento sem marcadores, reabilitação adaptativa,

avaliação da qualidade do movimento e personalização orientada pelo terapeuta numa plataforma de reabilitação unificada. O sistema proposto estabelece uma base tecnológica flexível para futura validação clínica da reabilitação do membro superior após acidente vascular cerebral. Como trabalho futuro, prevê-se a validação da plataforma com sobreviventes de acidente vascular cerebral, o aperfeiçoamento dos algoritmos de adaptação e de avaliação do movimento, bem como a exploração de tecnologias de captura de movimento mais recentes para aumentar a robustez e a aplicabilidade do sistema.

**Palavras-chave:** Acidente Vascular Cerebral • Jogos Sérios • Membros Superiores • Microsoft Kinect

# Abstract

Stroke is one of the leading causes of long-term disability worldwide, with upper-limb rehabilitation playing a fundamental role in promoting functional recovery and improving survivors' quality of life. However, conventional rehabilitation methods are often limited by clinical resource constraints, reduced therapy intensity, and difficulties in maintaining patient motivation and adherence throughout prolonged treatment periods. In this context, serious games and motion capture technologies have emerged as promising approaches for providing intensive, personalized, and motivating rehabilitation training. Despite significant advances in serious game design, motion tracking, adaptive training, and support for home-based therapy, many existing solutions still provide limited personalization, lack comprehensive movement-quality assessment, and do not fully integrate therapist supervision with adaptive rehabilitation.

This thesis presents the development, implementation, and preliminary evaluation of a Kinect-based serious game platform for upper-limb stroke rehabilitation. The proposed platform integrates four rehabilitation games targeting different motor functions within a closed-loop rehabilitation framework that combines real-time movement assessment, adaptive difficulty regulation, compensatory movement detection, multimodal feedback, and therapist-guided rehabilitation management. Patient-specific calibration is used to personalize the rehabilitation workspace, while computational movement-quality indicators inspired by the Fugl-Meyer Assessment for Upper Extremity (FMA-UE) and the Wolf Motor Function Test (WMFT) provide continuous objective performance assessment during gameplay. A dedicated therapist interface further supports exercise configuration, patient monitoring, and rehabilitation protocol customization.

A preliminary feasibility study involving 9 healthy volunteers, aged 19 to 87 years, was conducted to evaluate the platform's usability, functionality, user acceptance, motivation, game variety, instruction clarity, exercise difficulty, and perceived usefulness for rehabilitation prior to clinical testing. Participants completed rehabilitation sessions followed by quantitative and qualitative evaluation using Likert-scale questionnaires and open-ended comments. The platform received positive ratings across all evaluated dimensions, indicating that the proposed design provides an engaging, intuitive, and well-accepted rehabilitation experience. The evaluation also identified several technical limitations, including workspace personalization, posture-monitoring accuracy, and inherent limitations of the Kinect sensor, providing valuable guidance for future system refinement.

Although clinical effectiveness was not evaluated, the results demonstrate the technical feasibility of integrating serious games, markerless motion capture, adaptive rehabilitation, movement-quality assessment, and therapist-oriented personalization within a unified rehabilitation platform. The proposed system establishes a flexible technological foundation for future clinical validation of upper-limb stroke rehabilitation. Future work includes validating the platform with stroke survivors, improving the adaptation and movement-assessment algorithms, and investigating newer motion capture technologies to further enhance the robustness and applicability of the system.

**Keywords:** Stroke • Serious Games • Upper Limbs • Microsoft Kinect

# Acknowledgements

The completion of this dissertation would not have been possible without the support and guidance of several people to whom I would like to express my sincere gratitude.

First and foremost, I would like to thank Ana Filipa Nogueira for her supervision and for her role in the development of this work.

I would also like to thank Cláudia Rocha, Prof. Hélder Oliveira, and Prof. Luís Teixeira for their feedback, suggestions, and constructive discussions during the various meetings held throughout this project. Their insights helped improve both the technical and scientific quality of this work.

A special thank you is extended to Prof. Sara Stančín for her support during my Erasmus experience in Slovenia. Beyond the academic knowledge she shared, she contributed significantly to my personal and professional growth. The lessons learned during that period will remain with me throughout my career.

Finally, I would like to thank my mother and my sister for their unconditional support, patience, and encouragement throughout my academic journey. Their belief in me has always been a constant source of strength and motivation.

To all those who contributed, directly or indirectly, to the completion of this dissertation, I offer my sincere thanks.

This work was financed by Component 5 - Capitalization and Business Innovation of core funding for Technology and Innovation Centres (CTI), integrated in the Resilience Dimension of the Recovery and Resilience Plan within the scope of the Recovery and Resilience Mechanism (MRR) of the European Union (EU), framed in the Next Generation EU, for the period 2021-2026, with reference 21.

Filipa Morais

*“Life is what happens to you while you’re busy making other plans ”*

John Lennon

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# List of Abbreviations

|               |                                                                    |
|---------------|--------------------------------------------------------------------|
| <b>2D</b>     | Two-Dimensional                                                    |
| <b>3D</b>     | Three-Dimensional                                                  |
| <b>DC</b>     | Direct Current                                                     |
| <b>DFT</b>    | Discrete Fourier Transform                                         |
| <b>DDA</b>    | Dynamic Difficulty Adjustment                                      |
| <b>FAS</b>    | Functional Ability Scale                                           |
| <b>FMA</b>    | Fugl-Meyer Assessment                                              |
| <b>FMA-UE</b> | Fugl-Meyer Assessment - Upper Extremity                            |
| <b>FPS</b>    | Frames per Second                                                  |
| <b>IMUs</b>   | Inertial Measurement Units                                         |
| <b>IK</b>     | Inverse Kinematics                                                 |
| <b>KP</b>     | Knowledge of Performance                                           |
| <b>KR</b>     | Knowledge of Results                                               |
| <b>PRISMA</b> | Preferred Reporting Items for Systematic Reviews and Meta-Analyses |
| <b>RGB</b>    | Red-Green-Blue                                                     |
| <b>RGB-D</b>  | Red-Green-Blue and Depth                                           |
| <b>ROM</b>    | Range of Motion                                                    |
| <b>RGS</b>    | Rehabilitation Gaming System                                       |
| <b>SDG</b>    | Sustainable Development Goal                                       |
| <b>SDK</b>    | Software Development Kit                                           |
| <b>SPARC</b>  | Spectral Arc Length                                                |
| <b>ToF</b>    | Time-of-Flight                                                     |
| <b>VR</b>     | Virtual Reality                                                    |
| <b>WMFT</b>   | Wolf Motor Function Test                                           |

# Chapter 1

## Introduction

Stroke is an acute cerebrovascular disorder characterized by a sudden disruption of cerebral blood flow caused either by arterial occlusion (ischemic stroke) or intracranial haemorrhage (haemorrhagic stroke) [1]. In ischemic stroke, the obstruction of a cerebral artery leads to a reduction or complete cessation of blood supply, causing deprivation of oxygen and glucose, which ultimately results in neuronal cell death. In haemorrhagic stroke, the rupture of a blood vessel leads to bleeding within or around the brain within or brain tissue, producing both direct mechanical damage to neural tissue and secondary injury due to increased intracranial pressure and impaired cerebral perfusion. In both cases, these pathophysiological processes result in neuronal loss and subsequent impairment of neurological function.

Stroke incidence increases markedly with age, approximately doubling with each decade after the age of 55 [2], with a familial history of cerebrovascular events further elevating this risk.

According to the World Stroke Organization and the World Health Organization, stroke is currently the second leading cause of death and the third leading cause of disability worldwide [3, 4]. Epidemiological studies suggest that approximately one in four individuals will experience a stroke during their lifetime [4], illustrating the substantial global health burden associated with this condition.

The clinical consequences of stroke depend on the location and extent of brain injury, with neurological deficits emerging in body regions controlled by the affected cerebral areas. Among the neurological consequences of stroke, motor impairments are particularly prevalent and disabling [5]. Upper limb dysfunction is especially impactful, as the recovery of arm and hand function plays a crucial role in enabling individuals to regain independence, perform activities of daily living, and reconstruct a coherent sense of self following stroke [6].

Motor impairments after stroke are frequently accompanied by secondary musculoskeletal complications. Spasticity, affecting up to 60% of patients [7] is characterized by excessive and involuntary muscle activity that results in stiffness, restricted range of motion, and pain. If persistent, this hypertonicity, abnormal muscle stiffness, may lead to the development of fixed deformities, commonly referred to as contractures, which further restrict functional recovery and increase the risk of complications such as pressure ulcers.

Shoulder pain affecting the paralysed side after stroke is a common and disabling complication, affecting approximately 9% to 64% of patients depending on the rehabilitation setting and stage of recovery [8]. This condition can significantly restrict participation in rehabilitation and limit functional use of the affected limb.

In addition to shoulder pain, stroke survivors frequently develop flexion contractures of the wrist and hand. These impairments compromise grasping ability and manual dexterity, leading to significant functional limitations as well as aesthetic concerns [9]. Preventive and management strategies typically include passive and active range-of-motion exercises, splinting, and appropriate limb positioning.

Beyond musculoskeletal complications, stroke survivors frequently experience muscle weakness, impaired coordination, reduced proprioception, abnormal movement synergies, diminished voluntary movement selectivity, and psychological factors such as depression and apathy [10]. Collectively, these impairments contribute to long-term functional limitations and reduced spontaneous use of the affected upper limb.

In addition to these clinical challenges, stroke imposes a substantial economic burden, encompassing both acute treatment costs and long-term expenses related to post-discharge care and rehabilitation services [11]. This burden extends to patients, caregivers, and healthcare systems, further underscoring the need for rehabilitation approaches that are not only effective but also capable of improving adherence and long-term outcomes.

Effective motor recovery relies heavily on sustained, task-specific, and repetitive practice. Enhancing motivation during rehabilitation is therefore essential, particularly in patients presenting with low intrinsic engagement and significant upper limb impairments. Reduced motivation, fatigue, frustration, and perceived task difficulty often limit adherence to conventional therapy programs [12]. Evidence suggests that increased engagement and motivational support are associated with higher therapy intensity and improved motor outcomes. Interventions incorporating enriched environments, goal-oriented activities, and interactive training paradigms have demonstrated the potential to facilitate active participation and enhance neuroplasticity adaptation [13]. Neural plasticity constitutes the biological foundation of both learning in the intact brain and relearning in the damaged brain through rehabilitation [14].

Several non-invasive rehabilitation technologies have been introduced to enhance therapy precision, intensity, and personalization. These include robotic rehabilitation devices, Virtual Reality (VR) systems, functional electrical stimulation, brain-computer interfaces, and integrated digital rehabilitation platforms.

VR-based training enables patients to engage in interactive three-dimensional environments designed to promote upper limb strengthening and coordination. Through real-time monitoring and feedback, intelligent rehabilitation systems can provide personalized adjustments tailored to individual motor capabilities [15]. Systematic reviews indicate that VR-based interventions are safe and may be as effective as conventional physiotherapy for improving upper limb motor function after stroke [16–18].

Robot-assisted therapy has also demonstrated promising results [19], by enabling a higher number of repetitions within shorter time frames and improving movement precision, both factors that strongly influence rehabilitation outcomes.

Although numerous game-based and technology-assisted rehabilitation systems have been proposed, many lack clinically meaningful assessment mechanisms, adaptive personalization strategies, or tools that allow therapists to configure and monitor rehabilitation programs efficiently.

Stroke recovery is a dynamic and non-linear process in which the nature and severity of impairments evolve over time. Consequently, therapeutic interventions must be continuously adapted to target the impairments that most significantly limit functional performance at each stage of recovery. As highlighted by Raghavan [20], effective treatment strategies should be flexible and impairment-driven, ensuring alignment with the patient's evolving motor profile. Therefore, rehabilitation technologies must incorporate adaptive mechanisms and provide clinicians with intuitive tools for personalization and progression of therapy.

The objective of this thesis is to develop a serious game-based rehabilitation system designed to support upper limb recovery after stroke. The proposed system integrates interactive game-play with real-time performance feedback and customizable exercise configurations that can be adjusted by therapists according to the patient's rehabilitation needs. By combining motivational game design with adaptable rehabilitation exercises, the system aims to increase patient engagement, promote repetitive motor training, and support functional recovery.

## 1.1 Research Contributions

The main contributions of this thesis are summarized as follows:

### 1. Development of a Modular Closed-Loop Serious Game Platform for Upper-Limb Rehabilitation

A modular rehabilitation platform was designed and implemented, integrating Kinect-based motion capture, real-time performance assessment, adaptive difficulty regulation, therapist configuration tools, and four rehabilitation game modules within a unified architecture. The platform combines task-oriented training with principles of motor learning and experience-dependent neuroplasticity to support individualized upper-limb rehabilitation.

### 2. Patient-Specific Calibration for Personalized Rehabilitation

A calibration framework was developed to estimate each patient's functional upper-limb workspace using Kinect-based motion analysis. The resulting measurements are used to personalize rehabilitation tasks by adapting interaction boundaries according to the patient's available Range of Motion (ROM) from the beginning of each rehabilitation program.

### 3. Computational Assessment Framework Inspired by Clinical Outcome Measures

A computational movement assessment framework was proposed that translates selected movement components from the Fugl-Meyer Assessment - Upper Extremity (FMA-UE)

and Wolf Motor Function Test (**WMFT**) into kinematic metrics derived from markerless skeletal tracking. The framework additionally incorporates movement smoothness through the Spectral Arc Length (**SPARC**) metric, enabling continuous in-game assessment while explicitly treating the resulting scores as exploratory computational proxies rather than replacements for clinician-administered assessments.

#### **4. Real-Time Detection of Compensatory Movement Strategies**

A real-time posture-monitoring framework was developed to detect compensatory movement strategies, including forward trunk lean, lateral trunk inclination, and shoulder elevation, quantified relative to a patient-specific baseline established before each task or level within the rehabilitation modules. The detected compensation is incorporated into movement assessment while simultaneously providing multimodal corrective feedback intended to encourage appropriate movement execution during rehabilitation.

#### **5. Dual-Composite Adaptive Difficulty Framework**

An adaptive difficulty strategy was developed based on two independent composite performance scores computed from the same underlying rehabilitation metrics. One composite score is optimized for responsive gameplay adaptation, while the second emphasizes clinically relevant movement quality for longitudinal monitoring. This separation allows rehabilitation challenge to be adjusted without compromising the interpretability of clinical performance indicators.

#### **6. Therapist-Configurable Rehabilitation Authoring Environment**

A companion therapist application was developed for a game module to support the creation, visualization, modification, and management of individualized rehabilitation protocols without requiring modifications to the game source code. Rehabilitation exercises are represented using a structured JSON format, enabling customized therapy programs to be created, reused, and adapted according to individual patient needs without requiring software modifications.

#### **7. Integrated Patient Management and Longitudinal Rehabilitation Monitoring**

A persistent patient-management infrastructure was implemented to support longitudinal rehabilitation by storing calibration results, gameplay performance, movement assessment scores, rehabilitation history, and progression data across multiple sessions. This infrastructure enables individualized rehabilitation monitoring while supporting therapist-guided decision making throughout the rehabilitation process.

#### **8. Preliminary Feasibility and Usability Validation**

A preliminary feasibility evaluation involving healthy volunteers demonstrated the practical operation of the proposed platform under real-time conditions and provided evidence of favourable usability, engagement, and perceived rehabilitation value. The evaluation additionally identified important technical limitations, including posture-monitoring sensitivity



and workspace personalization, thereby informing future platform refinement prior to clinical evaluation with stroke survivors.

## 1.2 Contribution to the United Nations Sustainable Development Goals

This dissertation contributes primarily to the achievement of the United Nations Sustainable Development Goal (SDG) 3: Good Health and Well-Being. Stroke is one of the leading causes of long-term disability worldwide, making effective rehabilitation essential for improving functional recovery and quality of life. This work contributes to this goal through the design and implementation of a serious game-based rehabilitation platform that supports upper-limb motor training using markerless motion capture, real-time movement assessment, adaptive difficulty adjustment, and therapist-configurable rehabilitation exercises. By promoting engaging and personalized rehabilitation sessions, the proposed platform has the potential to support the delivery of rehabilitation services, although its clinical effectiveness remains to be established through future studies involving stroke survivors.

The proposed platform also contributes to SDG 9: Industry, Innovation and Infrastructure by integrating multiple digital health technologies within a single rehabilitation framework. The combination of Kinect-based motion tracking, automated performance evaluation, adaptive rehabilitation strategies, longitudinal data management, and therapist-oriented configuration tools represents an innovative approach to technology-assisted neurorehabilitation and demonstrates how interactive software can support the digital transformation of healthcare.

Finally, this work relates to SDG 10: Reduced Inequalities. By exploring a rehabilitation platform based on commercially available hardware and automated exercise supervision, the proposed system has the potential to improve access to rehabilitation, particularly for individuals who may face barriers to frequent in-person therapy. Although further clinical validation is required, the platform was designed with the long-term objective of supporting more accessible and personalized rehabilitation services.

## 1.3 Dissertation Structure

In addition to this introductory chapter, this dissertation is organized into six further chapters.

Chapter 2 presents the theoretical background relevant to this work, introducing the fundamental concepts of stroke rehabilitation, motor recovery, serious games, motion-capture technologies, and clinical assessment methods that underpin the proposed platform.

Chapter 3 reviews the state of the art by examining existing rehabilitation systems, serious games, motion-tracking technologies, and adaptive rehabilitation approaches. The limitations of current solutions are discussed, providing the motivation for the proposed platform.

Chapter 4 describes the methodology adopted in this work. It presents the design and implementation of the proposed rehabilitation platform, including the overall system architecture,

rehabilitation games, movement assessment framework, adaptive difficulty mechanism, therapist configuration tools, and other implementation details.

Chapter 5 presents the preliminary feasibility and usability evaluation conducted with healthy volunteers. It describes the evaluation methodology, participant characteristics, questionnaire design, and the quantitative and qualitative results obtained.

Chapter 6 discusses the findings of the preliminary evaluation, analyses the strengths and technical limitations of the proposed platform, and considers their implications for future clinical evaluation.

Finally, Chapter 7 summarizes the main contributions of this dissertation, presents the overall conclusions, and outlines directions for future work.

## Chapter 2

# Theoretical Background

This chapter presents the theoretical foundations underlying the design of serious game-based systems for upper-limb stroke rehabilitation. Effective rehabilitation depends on the interaction between neuroplastic adaptation, motor learning, behavioural factors, and feedback-driven task execution. Consequently, rehabilitation technologies must do more than simply encourage movement repetition; they must structure training conditions in ways that promote meaningful motor relearning while discouraging maladaptive compensatory behaviours.

These principles impose important design requirements on rehabilitation systems, including adaptive difficulty regulation, movement quality monitoring, task-specific interaction, and sustained patient engagement. Serious game-based rehabilitation systems are particularly relevant because they can integrate these mechanisms within interactive environments capable of delivering intensive, feedback-driven, and personalized therapy.

The concepts discussed throughout this chapter directly inform the architectural, interaction, and assessment decisions implemented in the proposed rehabilitation platform described in Chapter 4.

### 2.1 Neuroplasticity and the Biological Basis of Motor Recovery

Neuroplasticity constitutes the fundamental biological mechanism underlying post-stroke recovery. It refers to the capacity of the central nervous system to reorganize structurally and functionally in response to experience, environmental demands, and injury [21]. Following stroke, recovery depends not only on spontaneous biological repair processes but also on activity-dependent plasticity induced through rehabilitation interventions [22].

Functional improvement is strongly associated with repeated, task-oriented movement practice capable of promoting reorganization across distributed motor networks, including cortical and subcortical motor regions [23]. These adaptations support the reacquisition of motor function through reinforcement of residual neural pathways and motor relearning processes [24].

However, neuroplasticity is not inherently beneficial. Repeated execution of inefficient or compensatory movement strategies may reinforce maladaptive motor patterns rather than restore

physiologically appropriate movement control [25]. Consequently, rehabilitation systems must not only encourage high-volume movement practice, but also monitor movement quality and provide feedback capable of guiding patients toward more effective motor behaviours.

This distinction is particularly important in serious game-based rehabilitation systems, where successful task completion may otherwise be achieved through compensatory strategies that undermine long-term functional recovery.

## 2.2 Principles of Experience-Dependent Plasticity

Research in neurorehabilitation has identified a set of principles that govern how training experiences influence neural plasticity. These principles emphasize that recovery is strongly influenced by how rehabilitation activities are structured, including factors such as repetition, intensity, task specificity, and behavioural relevance. Collectively, they establish the conditions under which rehabilitation experiences are most likely to induce functional neural adaptation.

The key principles of experience-dependent plasticity relevant to rehabilitation, articulated by Kleim and Jones [14], are summarized in Table 2.1.

Table 2.1: Principles of experience-dependent plasticity

| Principle             | Description                                                                                    |
|-----------------------|------------------------------------------------------------------------------------------------|
| Use It or Lose It     | Failure to engage specific neural circuits can lead to degradation of those functions.         |
| Use It and Improve It | Repeated activation of neural circuits strengthens their function and promotes recovery.       |
| Specificity           | The nature of the training task determines the type of neural adaptation that occurs.          |
| Repetition Matters    | Induction of plasticity requires a sufficient number of repetitions.                           |
| Intensity Matters     | High training intensity is necessary to drive meaningful neural changes.                       |
| Time Matters          | Different mechanisms of plasticity are activated at different stages of recovery and training. |
| Salience Matters      | Training must be meaningful and engaging to effectively induce plastic changes.                |
| Age Matters           | Plasticity occurs more readily in younger individuals but remains possible throughout life.    |
| Transference          | Plasticity induced by one training task may facilitate performance of related tasks.           |
| Interference          | Some forms of training may interfere with the acquisition of other motor behaviours.           |

Therefore, these principles suggest that effective rehabilitation systems must support intensive and task-specific practice while continuously regulating challenge, feedback, and engagement. In technology-assisted rehabilitation, this requires systems capable of adapting task difficulty, monitoring performance quality, and maintaining meaningful interaction over prolonged training periods. Importantly, principles such as salience, specificity, and interference indicate that rehabilitation effectiveness depends not only on movement repetition, but also on how movement practice is structured and reinforced.

Evidence additionally suggests the existence of a temporally sensitive period following stroke during which the nervous system demonstrates increased responsiveness to rehabilitation interventions, particularly during the early subacute phase, approximately within the first weeks to three months after injury [26]. During this period, rehabilitation may induce enhanced neuroplastic adaptation due to increased neural excitability and spontaneous biological recovery processes. However, the precise boundaries of this critical window remain uncertain, and meaningful functional improvement can still occur during chronic stages when rehabilitation remains sufficiently intensive and task-specific.

Conventional rehabilitation programs are frequently constrained by factors such as therapist availability, limited session duration, patient fatigue, and reduced long-term adherence, potentially limiting the amount of intensive practice achievable in clinical settings [27]. Technology-assisted rehabilitation systems, particularly serious game-based approaches, may help address these limitations by enabling prolonged, feedback-driven, and adaptive training environments.

## **2.3 Motor Learning Theory and Skill Reacquisition**

Motor recovery after stroke is increasingly understood as a process of motor skill reacquisition rather than simple restoration of muscular strength. Contemporary motor learning theory conceptualizes recovery as an adaptive learning process in which movement execution, sensory feedback, reinforcement, and task interaction progressively shape motor behaviour [28]. From this perspective, successful rehabilitation depends not only on the amount of practice performed but also on how that practice is structured. Factors such as task difficulty, practice variability, feedback scheduling, and progression influence both motor skill acquisition and long-term retention [29]. Consequently, rehabilitation technologies should provide individualized and adaptive training environments capable of adjusting to the patient's evolving motor abilities.

### **2.3.1 Mechanisms of Motor Learning**

Motor recovery after stroke involves multiple complementary learning mechanisms, including error-based adaptation, reinforcement learning, and use-dependent plasticity [30]. Error-based learning occurs when discrepancies between intended and actual movement outcomes generate corrective adaptations that improve subsequent performance. Reinforcement learning strengthens movement behaviours that lead to successful task completion by increasing the likelihood that these behaviours will be repeated. In contrast, use-dependent plasticity arises through the repeated

execution of specific movements, gradually reinforcing the neural pathways associated with those movement patterns regardless of explicit error signals or external rewards [31, 32]. Together, these mechanisms highlight the importance of repetitive, task-oriented practice combined with meaningful feedback and appropriate task design.

Effective motor learning environments are typically characterized by several key elements [33]:

- **Active problem solving:** Engagement in tasks that require cognitive and motor decision-making.
- **Goal-directed behaviour:** Actions performed with a clear objective or outcome in mind.
- **Optimal challenge:** Tasks that are neither too easy nor too difficult, promoting learning.
- **Structured variability:** Variation in task conditions to enhance adaptability.
- **Appropriate feedback:** Timely and relevant information to guide performance and learning.

These mechanisms indicate that recovery depends not only on repeated movement execution, but also on conditions that support adaptation through feedback, reinforcement, and task interaction.

### 2.3.2 Regulation of Task Difficulty

An important component of motor learning is the regulation of task difficulty. Learning effectiveness depends not only on the type of movement practised, but also on the relationship between task demands and the learner's current capabilities. Excessively simple tasks provide insufficient challenge for adaptation, whereas excessively difficult tasks may overwhelm the learner and impair performance.

The Challenge Point Framework, proposed by Guadagnoli and Lee [34], provides a theoretical model for regulating task difficulty in motor learning environments. The framework distinguishes between nominal task difficulty and functional task difficulty.

Nominal task difficulty refers to the inherent complexity of the task itself, whereas functional difficulty reflects the challenge experienced by the learner based on their skill level and contextual factors. Optimal learning occurs when the functional difficulty of a task is appropriately matched to the learner's capabilities.

In rehabilitation environments, patient performance may fluctuate considerably across sessions due to fatigue, cognitive load, or recovery progression. Consequently, static difficulty progression may fail to maintain an appropriate challenge level throughout training. This limitation highlights the importance of rehabilitation systems capable of dynamically adapting task demands according to real-time user performance and condition.

### 2.3.3 Practice Structure and Contextual Interference

Practice is widely recognized as a fundamental determinant of motor skill acquisition [34]; however, the way practice is organized also influences the retention and transfer of the acquired motor skills. Two primary practice structures have been identified in motor learning research: blocked practice and random practice [35].

Blocked practice involves repeated execution of the same task under consistent conditions. While this approach often produces rapid improvements in immediate performance, it tends to result in weaker retention and limited transfer to novel situations. In contrast, random practice introduces greater variability and contextual interference by interleaving different tasks or movement patterns. Although this structure may initially degrade performance, it promotes deeper processing and enhances long-term learning and skill generalization.

For rehabilitation systems, this distinction highlights the importance of balancing immediate performance success with long-term learning outcomes. Training environments should therefore incorporate controlled variability that challenges the learner while still maintaining achievable goals [36].

### 2.3.4 Stages of Motor Learning

Motor learning evolves through multiple stages associated with changing cognitive and behavioural demands. Early stages of learning are typically characterized by high attentional demands, inconsistent performance, and strong dependence on external feedback, whereas later stages involve increasingly stable and automatic movement execution [37].

Because patients may progress through different learning stages throughout rehabilitation, the conditions that support motor recovery are not static. Effective rehabilitation systems must therefore adapt factors such as feedback frequency, task complexity, and environmental variability according to the patient's evolving capabilities and level of motor proficiency.

## 2.4 Behavioural Adaptations After Stroke

Motor recovery after stroke is influenced not only by neurological impairment itself but also by behavioural changes that emerge during the recovery process. These changes shape how individuals use their affected limb during daily activities and therapeutic exercises and may either support or hinder functional recovery.

Three major behavioural mechanisms affecting upper-limb recovery have been identified: (1) learned non-use, (2) learned maladaptive use, and (3) forgetting as determined by behavioural analysis of tasks [20].

Learned non-use, originally described by Edward Taub [38], occurs when repeated unsuccessful attempts to use the affected limb lead patients to rely increasingly on the unaffected limb. Over time, spontaneous use of the paretic limb decreases even when residual motor capacity remains.

Reduced use may further weaken cortical representation of the affected limb, reinforcing a cycle of disuse that limits recovery.

A related phenomenon is learned maladaptive use, in which patients develop compensatory movement strategies that allow them to accomplish tasks but do not reflect optimal motor control. Common examples include excessive trunk displacement, shoulder elevation, or increased reliance on proximal muscle groups to compensate for distal weakness. Although these strategies may improve short-term task performance, they can reinforce inefficient movement patterns and interfere with restoration of normal motor control.

The use-dependent forgetting mechanism refers to the gradual loss of motor improvements when newly acquired skills are not sufficiently practised or reinforced. Without continued activation of the neural pathways established during rehabilitation, previously achieved motor gains may deteriorate over time.

Collectively, these mechanisms demonstrate that recovery depends not only on biological repair processes but also on how patients interact with and use their remaining motor capabilities. This highlights the importance of rehabilitation approaches that encourage active use of the affected limb while discouraging ineffective compensatory behaviours.

## 2.5 Feedback and Engagement in Motor Rehabilitation

Effective rehabilitation requires not only execution of therapeutic movements but also sustained participation in meaningful practice. Feedback and motivational processes are closely interconnected, as feedback supports motor correction and learning while motivation influences persistence and adherence to therapy.

### 2.5.1 Augmented Feedback in Motor Relearning

Feedback plays a central role in motor relearning, particularly when intrinsic sensory information such as proprioception is impaired following stroke. Augmented feedback can provide additional information that helps patients evaluate performance and refine their movements.

Two major forms of augmented feedback are commonly described by Sharma [39]:

- **Knowledge of Results (KR):** Feedback concerning the outcome of a movement.
- **Knowledge of Performance (KP):** Feedback concerning the quality or kinematic characteristics of the movement.

In rehabilitation games, **KR** may be represented through task scores or completion indicators, whereas **KP** may involve real-time feedback regarding posture, trajectory accuracy, or compensatory movement execution.

According to the guidance hypothesis, excessively frequent feedback may create dependency and reduce the learner's ability to detect errors independently. Gradual reduction of feedback encourages development of internal error-detection mechanisms and supports long-term retention.



Digital rehabilitation systems frequently employ multimodal feedback, including visual, auditory, and sometimes haptic cues [40]. These approaches allow continuous monitoring of user behaviour and support adjustment of training conditions in response to patient performance.

### 2.5.2 Motivation and Engagement in Rehabilitation

Sustained engagement strongly influences rehabilitation outcomes because neuroplastic adaptation depends on repeated activation of neural pathways. One influential framework explaining sustained engagement is Self-Determination Theory, developed by Edward Deci and Richard Ryan [41]. According to this theory, intrinsic motivation is supported when three psychological needs are satisfied:

- **Autonomy:** The sense of control over one's actions.
- **Competence:** The perception of progress and mastery.
- **Relatedness:** Meaningful connection with others.

Rehabilitation environments that support these needs are more likely to sustain patient motivation and adherence to therapy.

Another relevant concept is Flow Theory, proposed by Mihaly Csikszentmihalyi [42]. Flow describes a psychological state of deep immersion that occurs when task difficulty is appropriately matched to an individual's skill level, promoting concentration and persistence during task performance.

In serious game-based rehabilitation systems, motivational mechanisms and feedback processes are often integrated within a shared interaction loop. Features such as performance indicators, adaptive difficulty, and reward systems can simultaneously support motor learning and encourage continued participation. Effective systems therefore require a balance between engaging game elements and clinically meaningful feedback that promotes correct movement execution.

## 2.6 Motion Capture and Kinematic Assessment in Rehabilitation

Assessment of upper-limb movement plays an important role in neurorehabilitation because it enables clinicians to evaluate impairments, monitor recovery progression, and identify compensatory behaviours [43, 44]. Although traditional assessments frequently rely on observational scales, advances in motion capture technologies have enabled objective quantification of movement characteristics such as joint angles, trajectories, range of motion, and movement smoothness [45, 46]. These capabilities have led to increasing integration of motion capture systems into rehabilitation platforms and serious games for movement assessment and real-time interaction.

### 2.6.1 Motion Capture in Rehabilitation

Motion capture refers to the process of digitally recording human movement for analysis and interaction [47]. In rehabilitation, motion capture systems are used to objectively quantify motor performance during therapeutic exercises and functional tasks.

Several categories of motion capture technologies are commonly employed in rehabilitation applications.

Wearable systems use sensors attached directly to the patient's body, including Inertial Measurement Units (IMUs), accelerometers, gyroscopes, and electromyography sensors [48]. These systems are often portable and relatively inexpensive but require sensor placement and physical attachment to the user.

Marker-based optical systems use multiple cameras to track reflective markers placed on anatomical landmarks. These systems provide highly accurate Three-Dimensional (3D) movement measurements and are widely considered the gold standard in biomechanical analysis. However, marker placement on bony landmarks is time-consuming and introduces inter- and intra-rater variability, as well as reduced session-to-session reliability [49]. In addition, these systems require controlled laboratory environments and extensive setup procedures, limiting their use in routine clinical or home-based rehabilitation settings.

Markerless systems estimate body postures without requiring physical markers or wearable devices [50]. Their reduced setup complexity and greater accessibility have increased their use in rehabilitation environments, particularly for home-based applications and interactive rehabilitation systems [51].

Each approach presents advantages and limitations related to accuracy, usability, cost, and practicality. Among these categories, markerless systems have received increasing attention because of their ability to support natural interaction while reducing setup requirements.

### 2.6.2 Markerless Motion Capture Technologies

Markerless motion capture technologies estimate human body posture without requiring physical markers or wearable sensors. Compared with traditional approaches, these systems reduce setup complexity and improve accessibility, making them increasingly attractive for rehabilitation applications.

One common category of markerless systems is based on Red-Green-Blue and Depth (RGB-D) cameras, which combine conventional Red-Green-Blue (RGB) imaging with depth sensing technologies. By estimating the distance between the camera and the user, these systems enable 3D reconstruction of body posture and movement. Commercial devices such as the Microsoft Kinect employ structured light (Kinect v1) or Time-of-Flight (ToF) (Kinect v2) sensing to acquire depth information, which is subsequently processed using computer vision algorithms to estimate real-time skeletal joint positions [52, 53].

Another important approach involves **RGB**-based pose estimation, which uses conventional cameras and machine learning algorithms to estimate body posture directly from image data. Modern frameworks such as OpenPose and MediaPipe employ deep learning methods to detect and track skeletal landmarks, providing either Two-Dimensional (**2D**) joint locations or estimated **3D** joint coordinates from **RGB** images [54]. Compared with depth-based systems, which generally provide more stable and accurate **3D** measurements for quantitative kinematic assessment, **RGB**-based approaches improve accessibility by eliminating the need for dedicated depth sensors and enabling movement tracking using standard consumer cameras. However, this increased accessibility is typically accompanied by reduced depth estimation accuracy and lower robustness during upper-limb movements involving substantial displacement along the depth axis or self-occlusion [53, 54].

Because markerless systems enable natural interaction without requiring physical attachment to the user, they are frequently employed in rehabilitation platforms for exercise monitoring, movement assessment, and feedback generation [55]. This characteristic may be particularly advantageous for stroke patients presenting reduced dexterity, spasticity, fatigue, or limited ability to independently position wearable sensors or markers.

### 2.6.2.1 Microsoft Kinect v2

The Microsoft Kinect v2 is a markerless motion capture device that has been extensively employed in rehabilitation research, human movement analysis, and serious game applications [56]. Originally developed as a motion-based interaction system for gaming, the sensor provides real-time full-body skeletal tracking without requiring wearable sensors, reflective markers, or specialized laboratory infrastructure [57]. These characteristics have contributed to its widespread adoption in rehabilitation systems aimed at movement monitoring, assessment, and interactive training.

As illustrated in Figure 2.1, the Kinect v2 combines a conventional **RGB** camera with a **ToF** depth sensor. The **RGB** camera provides colour images with a resolution of  $1920 \times 1080$  pixels, while the depth sensor captures depth information at a resolution of  $512 \times 424$  pixels [58]. By integrating depth measurements with computer vision and machine learning algorithms, the Kinect SDK estimates the spatial configuration of the human body and generates a real-time skeletal representation of the user.

The Kinect v2 skeletal model consists of 25 tracked joints distributed across the major body segments [58], as can be seen in Figure 2.1. Each tracked joint is represented by **3D** Cartesian coordinates relative to the Kinect sensor reference frame. These coordinates constitute the basis for computing joint angles, movement trajectories, inter-joint distances, and other kinematic variables used in rehabilitation assessment.

For upper-limb rehabilitation, the most relevant joints are the shoulder, elbow, wrist, and hand, as together they characterize reaching performance, joint kinematics, movement trajectories, **ROM**, and compensatory movement strategies [59]. These joints therefore constitute the primary source of kinematic information for quantitative movement assessment. Skeletal data are

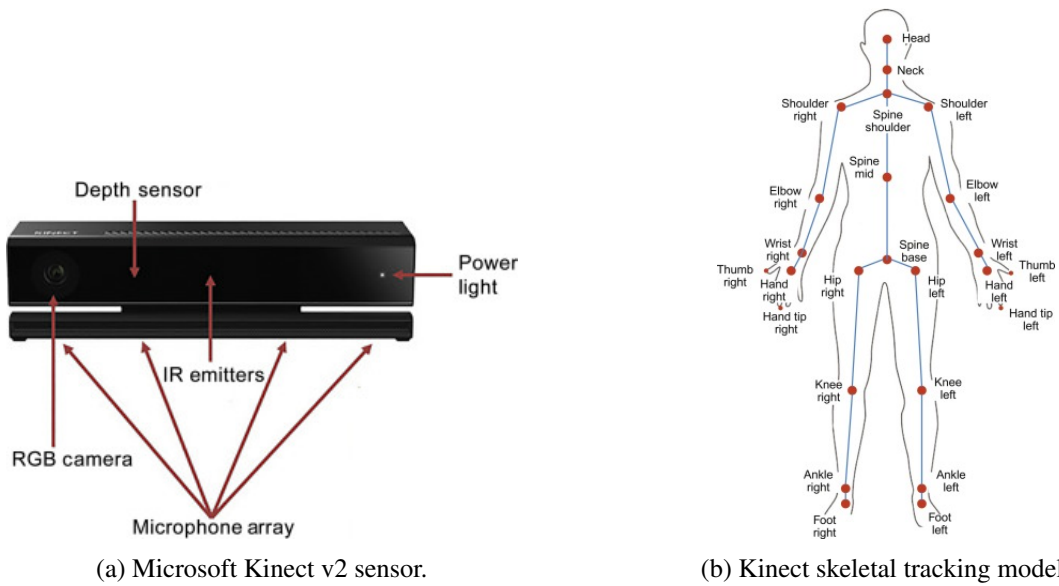


Figure 2.1: Microsoft Kinect v2 hardware and skeletal tracking representation. Reproduced from [58].

acquired at approximately 30 Frames per Second (FPS) [60], enabling continuous monitoring of movement during interactive rehabilitation exercises.

The Kinect v2 operates within a tracking range of approximately 0.5 m to 4.5 m, with optimal skeletal tracking generally achieved between 1.5 m and 3.5 m from the sensor [61]. These characteristics, together with its low cost and markerless operation, have contributed to its widespread adoption in clinical and home-based rehabilitation research [62].

Several studies have investigated the validity and reliability of Kinect-based motion tracking for rehabilitation and biomechanical applications. Although the sensor does not achieve the accuracy of laboratory-grade optical motion capture systems, it has demonstrated sufficient performance for the assessment of gross upper-limb movements, exercise monitoring, and interactive rehabilitation tasks [57]. Consequently, the Kinect v2 has become one of the most frequently reported motion capture technologies in rehabilitation-oriented serious games and virtual rehabilitation platforms.

Despite its advantages, several limitations must be considered. Skeletal tracking accuracy may decrease in situations involving self-occlusion, overlapping body segments, rapid movements, extreme joint configurations, or partial loss of visibility within the sensor field of view [63]. Furthermore, joint positions are estimated algorithmically from depth information and therefore represent approximations of anatomical joint centres rather than direct biomechanical measurements. As a result, Kinect-derived kinematic variables should be interpreted with consideration of the inherent uncertainty associated with markerless motion capture systems.

Although Microsoft has discontinued the Kinect product line, the Kinect v2 remains highly relevant within rehabilitation research due to its extensive validation in the literature, accessible software ecosystem, and large body of existing rehabilitation applications [64]. Consequently,

it continues to serve as an important reference platform for the development and evaluation of motion-based rehabilitation systems.

### 2.6.3 Kinematic Assessment of Upper-Limb Movement

Kinematic assessment refers to the quantitative analysis of human movement using spatial and temporal motion data [65]. In upper-limb rehabilitation, kinematic analysis is used to evaluate movement quality, monitor recovery progression, and identify compensatory movement strategies during therapeutic exercises.

One of the most commonly analysed movement parameters is **ROM**, which represents the angular displacement achieved by a joint during movement execution [66]. **ROM** measurements are frequently used to assess limitations in shoulder flexion, shoulder abduction, elbow extension, and other upper-limb movements commonly affected after stroke.

Joint angles constitute another important kinematic metric. By calculating the angular relationship between adjacent body segments, rehabilitation systems can estimate movement posture and evaluate motor performance during functional tasks [67]. Joint angle analysis is widely used to assess movement coordination and determine whether therapeutic exercises are performed correctly.

Movement trajectories describe the spatial path followed by a body segment or joint during movement execution. Analysis of movement trajectories provides information regarding reaching accuracy, motor control, and movement consistency throughout rehabilitation tasks [68, 69].

Movement smoothness is widely used as an indicator of motor control quality and coordination during upper-limb movement. Healthy reaching movements typically exhibit smooth, continuous trajectories with bell-shaped velocity profiles, whereas post-stroke movements often become fragmented and consist of multiple corrective sub-movements due to impaired motor planning, muscle weakness, and abnormal movement synergies [70].

Several kinematic metrics have been proposed to quantify movement smoothness, including jerk-based measures, the number of velocity peaks, and spectral-domain approaches. However, many traditional smoothness metrics are sensitive to movement duration, movement amplitude, and measurement noise. **SPARC**, introduced by Balasubramanian et al. [71], addresses several of these limitations by quantifying smoothness from the frequency spectrum of the movement velocity profile. Due to its robustness and sensitivity to changes in motor performance, **SPARC** has become increasingly popular in stroke rehabilitation research.

Smoothness measures can be used to objectively evaluate movement quality and monitor rehabilitation progression over time.

Another clinically important aspect of kinematic assessment is the detection of compensatory movements. During upper-limb rehabilitation, patients may compensate for motor impairments through excessive trunk displacement, shoulder elevation, or alternative movement strategies. Although compensatory behaviours may facilitate short-term task completion, they can interfere with

the recovery of physiologically appropriate movement patterns. Therefore, monitoring trunk displacement and other compensatory behaviours plays an important role in rehabilitation assessment and feedback systems.

By combining these kinematic measurements with real-time motion capture technologies, rehabilitation systems can provide objective movement analysis, support adaptive training strategies, and enable continuous monitoring of patient performance throughout the rehabilitation process.

## 2.7 Clinical Assessment of Upper-Limb Recovery

Accurate assessment of upper-limb motor function is essential in stroke rehabilitation, where clinicians rely on standardized instruments to quantify impairment level, functional ability, and recovery progression. Conventional assessment is typically based on therapist-administered ordinal scales, which, while clinically validated, remain partially subjective and may be insensitive to subtle kinematic changes [72].

Among the most widely used outcome measures are the **FMA-UE** and the **WMFT**, which together provide complementary information on motor impairment and functional task performance [73].

### 2.7.1 Fugl-Meyer Assessment (FMA-UE)

The **FMA-UE** consists of approximately 33 scored items evaluating upper-limb motor impairment following stroke. Each item is rated on a three-point ordinal scale (0 = cannot perform, 1 = partially performs, 2 = fully performs), resulting in a maximum score of 66 for the upper extremity component [74].

This assessment evaluates motor function across several domains, including reflex activity, voluntary movement performed within and outside flexor and extensor synergy patterns, wrist function, hand function, and coordination/speed [43, 75]. Assessment of voluntary movement focuses on the patient's ability to perform standardized movements involving the shoulder, elbow, forearm, wrist, and hand while demonstrating increasing movement selectivity and independence from pathological synergies. Each movement is scored according to the degree to which it can be completed under standardized testing conditions.

Because the **FMA-UE** relies primarily on visual observation of movement performance, several of its proximal upper-limb tasks can be objectively supported using motion-capture technologies. Quantitative measures such as joint angles, **ROM**, and movement trajectories have therefore been explored as complementary indicators to estimate performance in selected **FMA-UE** items and support automated rehabilitation assessment [76, 77].

### 2.7.2 Wolf Motor Function Test (WMFT)

The **WMFT** consists of 15 functional tasks and 2 strength-based items designed to evaluate upper-limb performance during goal-directed activities [78]. Tasks include reaching, lifting, object manipulation, and arm positioning under standardized conditions.

Each task is evaluated using two primary outcomes: (i) task completion time, measured from the initiation of movement to successful completion of the task-defined endpoint, and (ii) the Functional Ability Scale (**FAS**), a six-point ordinal rating ranging from 0 (no attempt) to 5 (normal movement) [79].

Unlike impairment-focused assessments such as the **FMA-UE**, the **WMFT** evaluates functional task performance through standardized goal-directed activities that involve coordinated movements of the shoulder, elbow, forearm, wrist, and hand [80].

Several **WMFT** tasks involve reaching and gross upper-limb transport movements that can be approximated using kinematic variables such as joint angles, endpoint trajectory, and movement duration [79]. However, tasks requiring object manipulation and grip control are less directly transferable to markerless motion tracking systems.

Together, the **FMA-UE** and **WMFT** provide complementary perspectives on upper-limb recovery, therefore serving as reference standards for the development of objective, sensor-based rehabilitation metrics.

### 2.7.3 Compensatory Trunk and Shoulder Movements After Stroke

Following a stroke, individuals often exhibit abnormal movement strategies during upper-limb tasks as a consequence of impaired motor control, reduced joint range of motion, and muscle weakness. These altered movement patterns are commonly described as compensatory motor behaviours, where proximal body segments are recruited to compensate for insufficient distal upper-limb function.

One of the most frequently observed compensatory strategies is increased trunk involvement during reaching tasks. In healthy individuals, reaching is predominantly achieved through coordinated shoulder and elbow motion with minimal trunk displacement. In contrast, post-stroke reaching is often characterised by excessive anterior trunk lean, lateral trunk displacement, and increased shoulder elevation. These compensations allow the hand to reach target positions despite reduced active shoulder flexion and elbow extension capacity [81].

Experimental studies have reported that individuals following stroke may exhibit trunk displacement during reaching that is substantially greater than that observed in unimpaired populations, with forward trunk lean and anterior translation occurring at levels up to approximately 4.5 times higher than normal during functional reaching tasks [82].

Shoulder elevation is another commonly observed compensatory mechanism [83], typically characterized by elevation of the shoulder and scapular girdle muscles. This pattern is often associated with reduced selective motor control at the shoulder joint and is used to assist arm elevation when shoulder flexion strength or coordination is limited.



Although these compensatory strategies enable task completion, they are generally considered suboptimal from a rehabilitation perspective, as they may reinforce maladaptive movement patterns and limit the recovery of isolated upper-limb motor control [84]. Consequently, contemporary rehabilitation increasingly seeks to quantify and minimize compensatory trunk and shoulder movements through objective kinematic assessment, promoting movement patterns that more closely resemble physiological upper-limb function [77].

Measures such as trunk displacement and shoulder elevation therefore provide valuable indicators of movement quality that complement traditional performance metrics, including task success and completion time. These kinematic measures are widely incorporated into computational rehabilitation systems for movement assessment, adaptive training, and real-time feedback aimed at discouraging compensatory strategies during upper-limb rehabilitation [76].

## 2.8 Serious Games in Neurorehabilitation

Digital technologies have increasingly been explored to address practical and motivational limitations associated with conventional rehabilitation. In this context, serious games are interactive digital applications designed for purposes beyond entertainment, including education, training, and rehabilitation [85]. Within neurorehabilitation, they embed therapeutic exercises into goal-oriented virtual activities that encourage active participation and repeated movement practice.

The adoption of serious games in stroke rehabilitation is motivated by several limitations of conventional therapy [17, 86, 87]. Rehabilitation exercises are often highly repetitive and may become monotonous over prolonged treatment periods, reducing patient engagement and adherence. In addition, therapist-supervised rehabilitation is constrained by available clinical resources and session duration, limiting the intensity and repetition of practice required to promote motor recovery. By transforming therapeutic exercises into interactive tasks, serious games seek to increase motivation while enabling high-frequency, task-specific movement practice [88].

Beyond increasing engagement, serious games can integrate several rehabilitation mechanisms within a single platform. They may provide real-time feedback, adapt task difficulty according to patient performance, maintain structured rehabilitation goals through gameplay, and continuously monitor movement during exercise execution [69]. When combined with motion-capture technologies, these systems can also generate quantitative kinematic data to support objective movement assessment and adaptive rehabilitation strategies.

From a rehabilitation engineering perspective, serious games have the potential to implement closed-loop rehabilitation paradigms, in which patient movements continuously influence the behaviour of the rehabilitation system while system-generated feedback guides subsequent motor performance. Such interactive feedback loops enable rehabilitation tasks to respond dynamically to user performance, supporting individualized training and adaptive rehabilitation strategies [69, 89].

However, the therapeutic effectiveness of serious games depends primarily on their rehabilitation design rather than their entertainment value. Unlike commercial games, success cannot be



measured solely by task completion or game score, as patients may achieve virtual objectives using compensatory movement strategies that do not promote motor recovery. Consequently, rehabilitation games should incorporate mechanisms that assess movement quality, identify compensatory behaviours, and provide feedback that encourages physiologically appropriate movement patterns instead of simply rewarding successful task completion.

Additional design considerations are also important. Excessive visual complexity, cognitively demanding interfaces, or poorly calibrated task difficulty may reduce accessibility for individuals with motor, sensory, or cognitive impairments after stroke [90]. Likewise, an excessive emphasis on reward mechanics may encourage strategies that optimize game performance without achieving the intended therapeutic objectives [91]. These challenges highlight the need to design rehabilitation games according to established principles of motor learning and clinical rehabilitation rather than entertainment objectives alone.

Overall, serious games should be regarded not merely as motivational tools, but as clinically oriented rehabilitation systems that integrate movement assessment, adaptive task regulation, motor learning principles, and meaningful feedback within a unified therapeutic framework. Their clinical value ultimately depends on how effectively gameplay mechanics support functional recovery while promoting high-quality movement.

## **2.9 Design Implications for Game-Based Rehabilitation Systems**

The theoretical concepts discussed throughout this chapter collectively indicate that effective rehabilitation systems must extend beyond simple movement repetition. Rehabilitation technologies should support task-oriented and high-repetition practice while simultaneously regulating movement quality, feedback, task difficulty, and patient engagement according to individual motor capabilities.

These requirements are particularly relevant in serious game-based rehabilitation environments, where therapeutic effectiveness depends not only on successful task completion but also on the quality of movement strategies reinforced during interaction. Consequently, rehabilitation systems must incorporate mechanisms capable of monitoring patient performance, adapting training conditions, and discouraging maladaptive compensatory behaviours throughout therapy.

From a system design perspective, these principles motivate the development of rehabilitation platforms that integrate real-time motion capture, adaptive difficulty regulation, quantitative movement assessment, and feedback-driven interaction within a unified closed-loop framework.

The theoretical foundations presented in this chapter therefore establish the conceptual basis for the rehabilitation system proposed in this thesis and directly inform the architectural and interaction design decisions.

## Chapter 3

# State of The Art

This chapter presents a structured review of the current state of the art in technology-assisted stroke rehabilitation, with a particular focus on serious game-based systems for upper limb recovery. The objective is to critically examine existing approaches, identify their strengths and limitations, and highlight gaps that motivate the present work.

### 3.1 Literature Search Strategy

The literature review was informed by Preferred Reporting Items for Systematic Reviews and Meta-Analyses (**PRISMA**)-style screening principles to support a structured and transparent study selection process. Relevant studies were identified through searches of PubMed and Scopus using combinations of keywords related to stroke rehabilitation, serious games, virtual reality, motor learning, motion tracking, and upper limb recovery.

Studies were included if they involved technology-assisted interventions targeting upper-limb motor rehabilitation after stroke, particularly systems incorporating interactive, game-based, or motion-tracking components. Studies focused exclusively on lower-limb rehabilitation, non-interactive interventions, or non-stroke populations were excluded.

The study selection process and screening results are summarized in Figure 3.1, which presents the **PRISMA** flow diagram used for article identification, screening, eligibility assessment, and final inclusion.

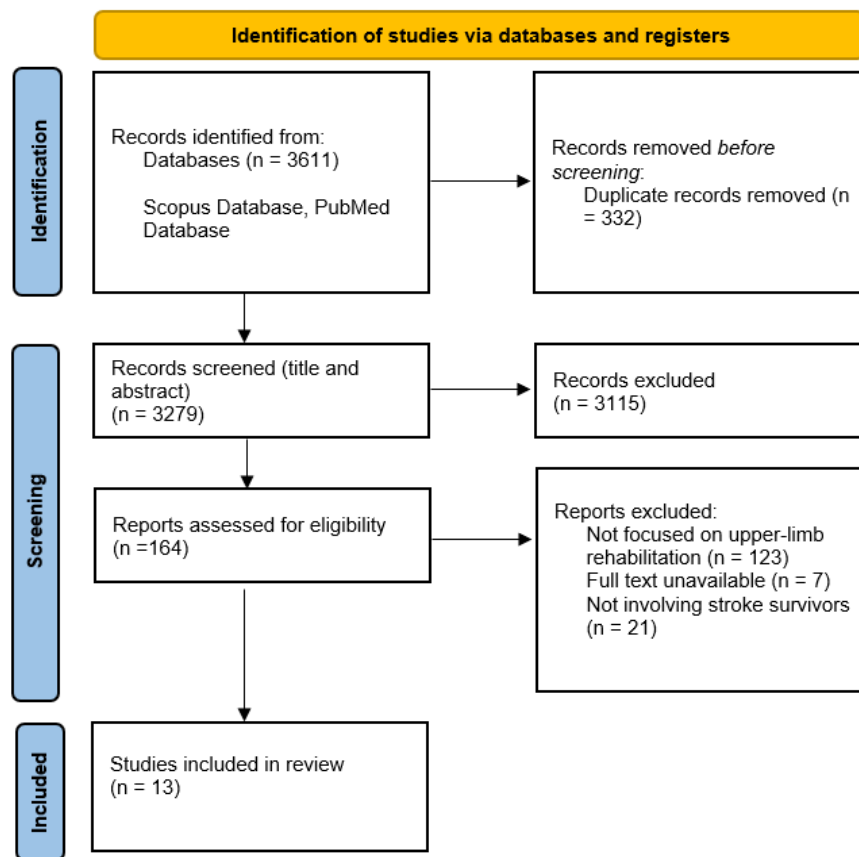


Figure 3.1: PRISMA flow diagram of study selection process.

## 3.2 Clinical Requirements for Effective Upper Limb Rehabilitation

Across clinical guidelines and systematic reviews, several core requirements for effective post-stroke rehabilitation consistently emerge [92–94]:

- High repetition and sufficient training intensity;
- Task specificity and functional relevance;
- Measurable progress and structured outcome monitoring;
- Ongoing therapist supervision and adaptation.

In conventional rehabilitation settings, therapy intensity is often constrained by limited clinical resources, therapist availability, and patient fatigue [95, 96]. As a result, the amount of task-specific practice performed by patients frequently falls below levels associated with optimal neuroplastic adaptation.

These limitations have motivated the development of technology-assisted rehabilitation systems, particularly serious game-based platforms, which aim to increase training intensity while

providing objective movement assessment, continuous feedback, and personalized rehabilitation. The following sections examine how existing systems address these clinical requirements and identify the limitations that continue to motivate further research.

### 3.3 Serious Games Developed for Upper-Limb Stroke Rehabilitation

The reviewed studies employ a wide variety of serious games to promote upper-limb rehabilitation, although most share the common objective of encouraging repetitive, task-oriented movements through interactive virtual environments. Despite this common goal, the proposed games differ substantially in their gameplay mechanics, therapeutic focus and degree of personalization.

Several rehabilitation systems are based on object interaction tasks that simulate functional reaching and grasping movements. RehabGame [97] requires users to collect virtual fruits and place them into a basket, promoting reach-and-grasp movements within a 3D environment while maintaining engagement through gamified interaction. Similarly, the Rehabilitation Gaming System (RGS) [69] incorporates progressively more complex object interaction tasks, beginning with object interception and advancing to grasping and object placement, thereby training reaching, grasping, release and manipulation skills. The Jintronix [98] platform also follows this approach through several rehabilitation games, including Kitchen, Catch-Carry-Drop and Fish Frenzy, which encourage repetitive reaching, lifting and object manipulation in simulated daily-life scenarios.

Other systems employ target-based exercises that focus on specific therapeutic movements. A Kinect-based rehabilitation game for frozen shoulder requires users to perform shoulder abduction until reaching predefined visual targets, following clinically prescribed rehabilitation exercises [99]. Likewise, Bubble Game promotes bilateral upper-limb rehabilitation by asking patients to simultaneously touch moving virtual bubbles, progressively increasing task difficulty by reducing bubble size and increasing movement speed [100].

Several studies adopted more personalized rehabilitation environments rather than fixed gameplay. Mystic Isle allows occupational therapists to configure individualized rehabilitation sessions according to each participant's functional goals, incorporating motor, cognitive and activities-of-daily-living exercises instead of predefined game scenarios [68]. Similarly, the virtual reality programme described by Bailey et al. [101] consisted of therapist-selected rehabilitation applications such as Rotate, Balloon Blast and Colour Match, each targeting different motor or cognitive rehabilitation objectives while being progressively adapted throughout treatment.

Other authors explored alternative game designs to increase motivation. Rodrigues et al. [102] transformed conventional rehabilitation exercises into a Tetris-inspired virtual reality game in which patients manipulate falling geometric blocks using upper-limb movements. Two gameplay modes were implemented to accommodate different levels of motor impairment while preserving the therapeutic objectives.

Beyond individual rehabilitation platforms, the systematic review by Aguilera-Rubio et al. highlighted the diversity of serious games developed for the Leap Motion Controller. Although

no standardized game library exists, the reviewed studies consistently incorporated exercises involving reaching, forearm pronation-supination, wrist flexion-extension, grasping, hand opening and closing, and finger movements through activities such as object manipulation, target reaching, balloon interaction, maze navigation and aircraft control. Overall, the review concluded that most serious games emphasize repetitive, task-oriented practice while using gamification to improve patient motivation and adherence [103].

Overall, the reviewed systems demonstrate that serious games can successfully transform repetitive rehabilitation exercises into engaging and motivating activities. Although gameplay mechanics vary considerably, most platforms emphasize task-oriented practice and patient adherence rather than standardized therapeutic content. The absence of common game design frameworks and the wide variation in rehabilitation tasks indicate that the effectiveness of serious games depends not only on gamification but also on how therapeutic principles are integrated into the game design.

### 3.4 Motion Capture Technologies

The reviewed rehabilitation systems employ a variety of motion capture technologies to monitor upper-limb movements, ranging from markerless optical sensors to wearable devices and immersive virtual reality controllers. Many systems prioritize natural interaction by avoiding handheld controllers or markers while providing sufficient movement accuracy for rehabilitation.

Markerless optical tracking based on the Microsoft Kinect was the most frequently adopted solution. RehabGame combines Kinect V2 skeletal tracking with the Myo armband to monitor both upper-limb kinematics and muscle activity during rehabilitation exercises [97]. Other Kinect-based systems rely exclusively on skeletal tracking to quantify rehabilitation movements. For example, one system estimates shoulder abduction by calculating joint angles from the shoulder, elbow and spine positions [99], while Bubble Game uses Kinect to capture bilateral arm movements during gameplay without requiring external controllers [100]. Similarly, both Jintronix and Mystic Isle employ Kinect depth sensing to track body movements in three-dimensional space, allowing patients to interact naturally with rehabilitation games while enabling therapists to remotely monitor performance and adjust rehabilitation programmes [68, 98].

Some rehabilitation platforms combine multiple sensing modalities to capture more detailed movement information. The RGS integrates the Analysis and Tracking System (AnTS), which tracks coloured markers attached to the wrists and elbows, with 5DT data gloves to detect finger flexion and grasping movements. The captured data are mapped in real-time onto a virtual avatar that mirrors the patient's upper-limb movements [69]. RehabGame similarly complements Kinect skeletal tracking with a Myo armband that records electromyography, accelerometer, gyroscope and orientation data, allowing simultaneous monitoring of limb motion and muscle activation [97].

Immersive virtual reality systems employ dedicated motion-tracking hardware instead of optical body tracking. Ferreira et al. used an Oculus Rift head-mounted display together with

Razer Hydra motion controllers to continuously capture the position and orientation of the patient's hands. Before each session, the virtual workspace is calibrated according to the patient's available range of motion to ensure accessible interaction [102]. Similarly, the telerehabilitation programme described by Bailey et al. combined a virtual reality headset with proprietary rehabilitation software, enabling therapists to remotely supervise patient movements while automatically recording movement quality, shoulder range of motion and temporal performance metrics [101].

The systematic review by Aguilera-Rubio et al. focused on rehabilitation systems based on the Leap Motion Controller. Unlike Kinect-based approaches, the Leap Motion Controller specializes in tracking hand, wrist and forearm movements using infrared optical cameras, enabling precise interaction with virtual objects without requiring wearable sensors or handheld controllers. Across the reviewed studies, the device was successfully employed in both clinical and home-based rehabilitation settings, with some systems incorporating remote therapist monitoring for telerehabilitation [103].

Taken together, the reviewed literature demonstrates a clear preference for markerless motion capture technologies, particularly Kinect and Leap Motion, because they enable natural interaction without wearable sensors. Although different sensing modalities provide varying levels of kinematic detail, most platforms successfully capture movement data suitable for rehabilitation. Nevertheless, accurately capturing movement does not necessarily imply that the collected data are translated into clinically meaningful assessment or adaptive rehabilitation decisions, a limitation that remains evident across many existing systems.

### 3.5 Feedback Mechanisms

Feedback is a fundamental component of serious game-based rehabilitation, supporting motor learning, maintaining patient motivation and enabling objective monitoring of rehabilitation progress. Across the reviewed studies, feedback mechanisms can be broadly categorized into immediate visual feedback, quantitative performance feedback, therapist-mediated feedback and motivational elements.

Immediate visual feedback was virtually incorporated by all rehabilitation systems. Most platforms represent the patient's movements using a virtual avatar or interactive virtual objects, allowing users to immediately observe the consequences of their actions. RehabGame mirrors the user's movements through a full-body avatar while providing colour changes, rotating targets and warning messages whenever movements exceed predefined anatomical constraints [97]. Similarly, RGS displays a virtual avatar that reproduces the patient's arm movements in real-time during interception, grasping and object placement tasks [69], while Jintronix and Mystic Isle provide continuous visual feedback through interactive rehabilitation games that reflect the user's movements throughout each session [68, 98]. Simpler systems rely on visual targets to guide movement execution, such as the Kinect-based shoulder rehabilitation game, which indicates the desired shoulder elevation angle [99], and Bubble Game, where moving bubbles provide intuitive visual cues for bilateral reaching tasks [100].

Many systems also provide quantitative performance feedback by automatically recording rehabilitation metrics throughout gameplay. Commonly monitored variables include movement speed, movement accuracy, task completion, game scores and repetition counts [68, 69, 98]. Bubble Game additionally records hit and miss rates, bubble size and hand usage, presenting the results as graphical performance reports that allow users and clinicians to monitor progress across sessions [100]. The virtual reality programme described by Bailey et al. records movement quality, shoulder range of motion, response time and action time, enabling objective assessment of rehabilitation progress over time [101]. Likewise, Ferreira et al. monitor movement amplitude, total movement distance, gameplay duration and scores during rehabilitation sessions [102].

Several rehabilitation platforms extend feedback beyond the patient by incorporating therapist supervision. Home-based systems such as Jintronix, Mystic Isle and the telerehabilitation platform described by Bailey et al. enable therapists to remotely review objective performance metrics, monitor adherence and modify rehabilitation programmes according to patient progress [68, 98, 101]. In Bailey et al., therapists additionally provide real-time verbal feedback during supervised sessions, complementing the automated feedback generated by the virtual reality platform [101].

Besides supporting motor learning, many systems incorporate motivational feedback through gamification. Performance scores, successful task completion, progression indicators and interactive virtual environments encourage continued participation and reinforce correct movement execution [97, 100, 102]. The systematic review by Aguilera-Rubio et al. similarly concluded that most Leap Motion-based rehabilitation systems combine immediate visual feedback with quantitative performance monitoring and, in home-based settings, remote therapist supervision, highlighting feedback as one of the principal mechanisms supporting patient engagement and rehabilitation progress [103].

Overall, feedback mechanisms primarily aim to motivate patients through visual interaction and performance scores while providing therapists with objective performance summaries. However, few systems provide clinically meaningful corrective feedback based on movement quality, limiting the ability of feedback to directly improve movement execution during rehabilitation.

### 3.6 Adaptive Rehabilitation Strategies

Adaptive rehabilitation strategies ranged from fully automatic algorithms to therapist-guided personalization, while some systems relied solely on predefined difficulty progression.

Several studies implemented automatic adaptation based on patient performance. RehabGame employed a Monte Carlo Tree Search (MCTS) algorithm to dynamically generate new target positions according to previous movement trajectories, progressively increasing exercise difficulty while maintaining safe movement limits [97]. Similarly, the Kinect-based shoulder rehabilitation game predicted the next target shoulder angle using historical performance data, comparing Exponential Smoothing and Kalman Filter approaches. Exponential Smoothing achieved superior prediction accuracy and was adopted for adaptive target generation [99].



More comprehensive adaptive frameworks were implemented in rehabilitation-specific platforms. **RGS** incorporated a Personalized Training Module (PTM), which first calibrated each patient's movement capabilities and then continuously adjusted task difficulty according to performance. Difficulty increased when patients successfully completed more than 70% of the tasks and decreased when performance fell below 50%, with independent adaptation for the paretic and non-paretic limbs [69]. Likewise, the virtual reality Tetris-based game adapted the rehabilitation workspace through an initial calibration procedure and implemented Dynamic Difficulty Adjustment (DDA), automatically reducing gameplay difficulty after prolonged unsuccessful attempts to maintain patient motivation. Therapists could additionally select different gameplay modes according to the patient's rehabilitation stage [102].

In contrast, several systems relied primarily on therapist-guided personalization rather than autonomous adaptation. Jintronix allowed physiotherapists to configure game selection, movement trajectories, range of motion and exercise difficulty according to each participant's functional abilities, with remote adjustments performed throughout treatment [98]. Similarly, Mystic Isle was customized according to rehabilitation goals identified using the Canadian Occupational Performance Measure (COPM), enabling therapists to modify exercise type, repetitions, challenge level and game parameters based on patient progress [68]. The virtual reality-assisted rehabilitation programme described by Bailey et al. also depended on therapist supervision, with clinicians remotely selecting rehabilitation activities and progressively adjusting parameters such as activity type, grid size and exercise speed according to functional improvements [101].

Not all rehabilitation systems incorporated patient-specific adaptation. The Bubble Game increased task difficulty by progressively reducing bubble size and increasing movement speed throughout gameplay, but this progression followed predefined rules rather than adapting to individual performance [100].

The systematic review by Aguilera-Rubio et al. confirmed that adaptive rehabilitation remains highly heterogeneous across the literature. Existing systems employ a wide range of progression strategies, including automatic performance-driven algorithms, therapist-controlled personalization and predefined game progression, with no standardized framework currently adopted across rehabilitation platforms [103].

Across the reviewed literature, adaptive rehabilitation remains highly heterogeneous across existing platforms. While several systems incorporate either automatic difficulty adjustment or therapist-guided personalization, few combine algorithm-driven adaptation with detailed movement assessment and continuous clinical supervision within a unified adaptive framework. Furthermore, although therapists are commonly able to adjust predefined game parameters such as exercise difficulty, range of motion or task selection, relatively few systems support the creation of flexible rehabilitation protocols that integrate customizable exercises, assessment criteria and adaptive rehabilitation strategies.



### 3.7 Evaluation Methodology

The reviewed studies employed evaluation methodologies ranging from preliminary technical validation to randomized controlled clinical trials, reflecting different stages of rehabilitation system development.

Early-stage studies primarily focused on validating technical feasibility rather than clinical effectiveness. RehabGame was evaluated using two participants to verify the adaptive target generation algorithm while recording joint positions, joint angles, movement velocity, electromyography (EMG), accelerometer and gyroscope signals. Although the adaptive algorithm successfully generated coherent movement trajectories with progressively increasing difficulty, the absence of stroke participants and the extremely small sample size prevented conclusions regarding therapeutic effectiveness [97]. Similarly, the Kinect-based shoulder rehabilitation system was evaluated using gameplay data from five participants to compare two adaptive prediction methods. Exponential Smoothing achieved higher prediction accuracy (91.01%) than the Kalman Filter (87.59%), although no clinical outcomes or motor recovery measures were assessed [99].

Several studies conducted usability or pilot evaluations involving healthy volunteers or relatively small groups of stroke survivors. The Bubble Game was assessed with 15 healthy participants to evaluate gameplay performance and user experience. The authors reported good usability and engagement, while observing expected differences in movement performance between younger and older participants [100]. Similarly, the immersive Tetris-based rehabilitation game was evaluated through a pilot study involving 15 stroke patients. User Experience Questionnaire (UEQ) results indicated high engagement and motivation, while therapists considered the system a useful complement to conventional rehabilitation despite the need for larger clinical studies [102]. Mystic Isle was evaluated through a six-week feasibility study involving four chronic stroke survivors. Besides usability measures such as the System Usability Scale and Game Experience Questionnaire, clinical assessments including the FMA-UE, Canadian Occupational Performance Measure (COPM), Activities-specific Balance Confidence Scale (ABC) and Stroke-Specific Quality of Life Scale (SS-QOL) were collected. Although participants reported high satisfaction with the personalized rehabilitation programme, the study primarily demonstrated feasibility rather than clinical effectiveness [68]. A virtual reality-assisted rehabilitation programme was also reported as a single-patient case study, showing improvements in upper-limb strength, range of motion, movement quality and activities of daily living. However, the absence of a control group and the single-subject design considerably limit the generalizability of the findings [101].

Stronger clinical evidence was provided by randomized controlled trials. RGS was evaluated in a 12-week randomized controlled pilot study involving acute stroke patients. Compared with conventional rehabilitation or non-specific interactive games, participants using RGS demonstrated significantly greater improvements in paretic arm speed, proximal upper-limb motor function measured by the FMA-UE, and functional performance assessed using the Chedoke Arm and Hand Activity Inventory (CAHAI). Participants also reported high acceptance and willingness to continue therapy using the system [69]. The Jintronix platform was evaluated in a larger single-

blind randomized controlled trial involving 51 chronic stroke survivors. Although no statistically significant differences were observed between Jintronix and the conventional GRASP home exercise programme on the primary clinical outcomes, participants completing the recommended training dosage achieved greater clinically meaningful improvements in **FMA-UE** scores. The study additionally demonstrated high adherence, low pain and fatigue, and confirmed the feasibility of home-based virtual reality rehabilitation [98].

The systematic review by Aguilera-Rubio et al. summarized evidence from six studies involving 144 stroke survivors across acute, subacute and chronic rehabilitation phases. The review highlighted considerable heterogeneity in intervention duration, outcome measures and study design, ranging from pilot studies to randomized controlled trials. Despite these methodological differences, most studies reported improvements in upper-limb function, dexterity, strength and patient engagement following Leap Motion-based rehabilitation. Nevertheless, the review emphasized that small sample sizes, inconsistent evaluation protocols, limited follow-up and moderate methodological quality remain important limitations, reinforcing the need for larger and more rigorous clinical validation studies [103].

Collectively, the reviewed studies demonstrate encouraging results regarding feasibility, usability and clinical potential. Nevertheless, much of the evidence remains based on pilot studies, small sample sizes and heterogeneous evaluation methodologies, making direct comparison between rehabilitation systems difficult and highlighting the need for more rigorous and standardized clinical validation.

These observations are further supported by recent systematic reviews and umbrella reviews. Voinescu et al. and Stan et al. [104, 105] concluded that virtual reality interventions consistently improve upper-limb motor recovery, particularly when combined with conventional rehabilitation, although the overall certainty of evidence remains low to moderate due to methodological heterogeneity. Likewise, Doumas et al. [106] demonstrated that serious games produce greater improvements than conventional therapy when they integrate multiple evidence-based neurorehabilitation principles, such as adaptive difficulty, continuous feedback and task-specific practice.

### 3.8 Research Gap

The literature reviewed throughout this chapter demonstrates that substantial progress has been made in technology-assisted upper-limb stroke rehabilitation. Existing systems successfully employ serious games to increase patient motivation, integrate a range of motion capture technologies to objectively monitor movement, provide real-time visual feedback, and support home-based rehabilitation through adaptive training strategies and remote therapist supervision. Systematic reviews further indicate that these technologies can improve upper-limb motor recovery, particularly when combined with conventional therapy and when designed according to established neurorehabilitation principles.

Despite these advances, current rehabilitation platforms remain largely fragmented in their design. The reviewed systems successfully implement one or more key rehabilitation components, such as engaging serious games, quantitative movement monitoring, adaptive difficulty adjustment, or therapist-guided personalization, but few integrate these capabilities into a single coherent rehabilitation framework. Consequently, assessment, adaptation, feedback and therapist decision-making often operate as separate processes rather than as interconnected elements of rehabilitation.

A particularly important limitation concerns movement assessment. Although many systems collect kinematic data during rehabilitation sessions, these measurements are frequently used only for post-session performance analysis or basic scoring. Relatively few platforms perform clinically meaningful movement-quality assessment, detect compensatory movement strategies in real-time, or use these analyses to directly influence rehabilitation progression. Similarly, most feedback mechanisms remain focused on task completion, scores or visual interaction, while personalized corrective feedback based on movement quality is comparatively uncommon.

Adaptive rehabilitation also remains highly heterogeneous across the literature. Existing systems employ predefined difficulty progression, algorithm-driven adaptation or therapist-controlled customization, but rarely combine automatic adaptation with clinically informed therapist supervision. As a result, rehabilitation progression is often based primarily on task success rather than on a comprehensive evaluation of movement quality, functional performance and patient-specific rehabilitation goals.

The findings from the reviewed systematic reviews reinforce this limitation. Rehabilitation systems incorporating multiple evidence-based neurorehabilitation principles, including task-specific practice, adaptive difficulty, continuous feedback and individualized training, consistently demonstrate superior clinical outcomes. However, few existing platforms simultaneously integrate these principles with objective movement-quality assessment, compensatory movement detection, therapist-configurable rehabilitation protocols and real-time adaptive decision-making.

Therefore, the principal challenge is no longer the development of engaging rehabilitation games or the acquisition of movement data. Instead, future rehabilitation platforms should function as integrated closed-loop rehabilitation systems, in which motion capture, movement-quality assessment, compensatory movement detection, adaptive exercise progression, therapist supervision and real-time corrective feedback continuously interact to personalize therapy according to each patient's motor performance. Addressing this challenge constitutes the primary motivation for the system proposed in this dissertation.

## **Chapter 4**

# **Design and Development of the Rehabilitation Platform**

The development methodology followed an iterative design-science approach combining clinical rehabilitation principles, motion capture technologies, and adaptive game-based interaction design. The system architecture was progressively refined through integration of biomechanical tracking, rehabilitation assessment models, and therapist-centred personalization mechanisms. The implementation process emphasized modularity, reproducibility, and clinical applicability.

Therefore, this chapter describes the design and implementation of the proposed rehabilitation platform. It first introduces the overall rehabilitation framework and its shared components, including patient calibration, movement monitoring, performance evaluation, clinical assessment, and compensation detection. Subsequently, the adaptive rehabilitation framework responsible for dynamic difficulty adjustment based on patient performance is presented. Finally, the four rehabilitation game modules are described in detail.

### **4.1 System Overview and Requirements**

The proposed platform was developed as a closed-loop rehabilitation system intended to support upper-limb motor recovery through adaptive serious game interaction. The system architecture was designed to operationalize rehabilitation principles derived from neuroplasticity and motor learning theory, including task-oriented practice, high repetition, performance feedback, movement quality monitoring, and therapist-guided personalization. By combining real-time motion capture with interactive rehabilitation activities and quantitative performance assessment, the platform aims to promote patient engagement while supporting clinically meaningful motor training.

The system was designed around three primary objectives: continuous monitoring of upper-limb movement, adaptive regulation of rehabilitation difficulty, and integration of rehabilitation-oriented performance assessment within an interactive rehabilitation environment. To achieve these objectives, four principal functional requirements were defined:

- **Real-time movement tracking:** To enable continuous acquisition of upper-limb kinematics during exercise execution.
- **Interactive rehabilitation activities:** Capability of transforming therapeutic movements into engaging game-based tasks.
- **Objective movement assessment:** To provide clinically relevant performance metrics derived from skeletal tracking data.
- **Therapist-driven personalization:** To allow exercises and task parameters to be adapted according to individual patient capabilities and rehabilitation goals.

To satisfy these requirements, the system integrates the Microsoft Kinect v2 sensor, a Unity-based rehabilitation environment, an assessment framework inspired by established clinical scales, and an adaptive task management system capable of modifying exercise difficulty according to patient performance.

Figure 4.1 presents an overview of the proposed rehabilitation platform. The system comprises four rehabilitation game modules, each designed to target complementary aspects of upper-limb motor recovery while sharing a common framework for patient calibration, movement monitoring, clinical assessment, compensation detection, and performance evaluation. Although each module presents a different therapeutic task, all operate on the same underlying architecture and use the same Kinect-based motion capture and assessment pipeline.

During a rehabilitation session, the Kinect sensor captures the patient's movements and transmits skeletal data to the Unity application. The rehabilitation modules use this information to drive real-time interactions within the virtual environment, while the assessment framework continuously evaluates movement quality and task performance. The resulting performance metrics are stored and presented through a therapist interface, supporting longitudinal monitoring and exercise personalization.

Together, these subsystems establish a continuous sensing-assessment-adaptation loop in which patient performance directly influences rehabilitation task configuration and therapeutic progression. This closed-loop architecture allows the rehabilitation environment to dynamically respond to patient capabilities while maintaining clinically relevant movement practice conditions.

The proposed rehabilitation platform was developed as an extension and substantial redesign of a previously developed rehabilitation prototype system [107]. Certain foundational components from the earlier implementation were retained and expanded within the present work, including portions of the database structure, user authentication and credential management mechanisms, selected avatar assets, and the conceptual basis of the capsule-based rehabilitation module.

However, the current dissertation extends the original platform through the introduction of a modular closed-loop rehabilitation architecture integrating patient-specific calibration procedures, adaptive difficulty regulation mechanisms, real-time movement analysis, compensation monitoring strategies, therapist-driven rehabilitation personalization, and movement assessment methodologies inspired by the **FMA-UE** and **WMFT**. Because several assessment items contained in the

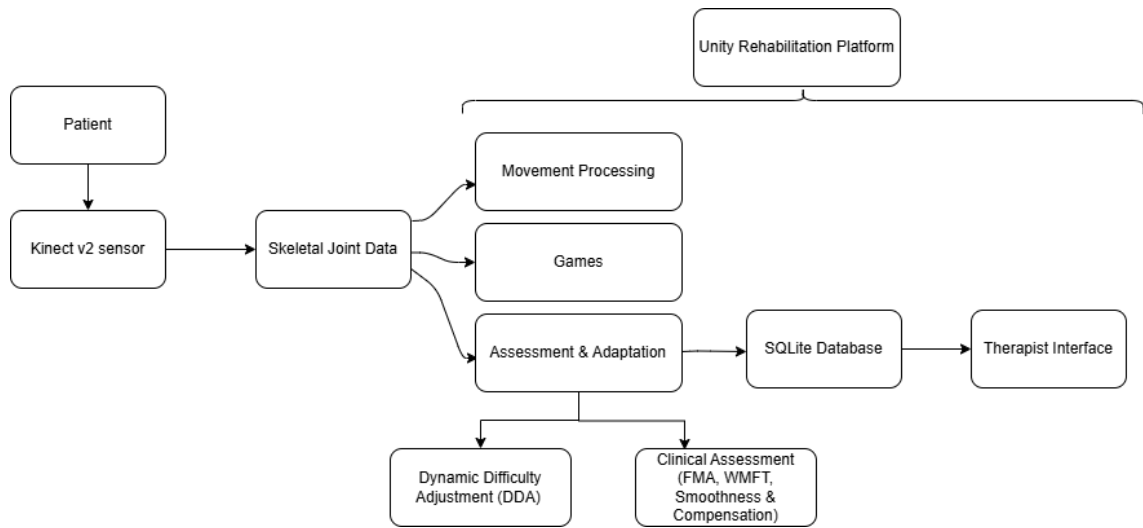


Figure 4.1: Overall architecture of the rehabilitation platform.

original clinical scales require direct clinical observation, manual evaluation, or measurements that cannot be reliably obtained using markerless skeletal tracking, the implemented framework does not constitute a digital reproduction of either assessment instrument. Instead, the generated scores should be interpreted as exploratory computational indicators of movement performance and rehabilitation progression. These metrics are intended to complement rehabilitation monitoring and therapist review rather than replace standardized clinical assessment procedures, clinical diagnosis, or therapeutic decision-making.

Additionally, the rehabilitation modules, interaction logic, adaptive progression framework, movement evaluation pipeline, feedback mechanisms, and overall software architecture were substantially redesigned and expanded to support individualized upper-limb rehabilitation within an integrated serious-game environment.

## 4.2 System Architecture

The rehabilitation platform was implemented using a modular closed-loop architecture designed to support real-time motion tracking, rehabilitation interaction, movement assessment, and adaptive exercise regulation within a unified software environment. The architectural design emphasizes separation between sensing, processing, interaction, and assessment components in order to improve extensibility, maintainability, and integration of rehabilitation-specific functionalities.

The platform was developed in the Unity game engine using C# as the primary programming language. The Microsoft Kinect v2 sensor and the Kinect for Windows Software Development Kit (SDK) were used to acquire real-time 3D skeletal joint data, enabling patient interaction with the rehabilitation games, movement processing, and clinical performance assessment. Patient profiles, calibration results, assessment metrics, gameplay statistics, and rehabilitation progression data were stored within an integrated SQLite database.

Within Unity, the skeletal data are processed through a centralized motion processing pipeline responsible for extracting rehabilitation-relevant kinematic features, including joint angles, reach distances, trunk displacement, movement trajectories, and workspace boundaries. These features are then made available to the rehabilitation modules, assessment framework, and adaptive difficulty system through a common software architecture.

The rehabilitation game modules operate as the primary interaction layer of the system. Patient movements captured by the Kinect sensor are mapped in real-time to virtual interactions within the rehabilitation environment, allowing therapeutic exercises to be performed through gameplay activities. Each game module accesses the processed kinematic data to evaluate task execution, regulate interaction logic, and provide visual and auditory feedback during rehabilitation exercises.

Assessment outputs are provided to the adaptive difficulty framework, which regulates task complexity according to patient performance. Depending on the rehabilitation module, parameters such as target size, object velocity and movement precision thresholds may be adjusted dynamically. The objective is to maintain an appropriate level of challenge while accommodating patient-specific capabilities and rehabilitation progression.

This modular design facilitates system extensibility while enabling personalized rehabilitation experiences driven by real-time movement analysis.

## **4.3 System Workflow and User Roles**

The rehabilitation platform was designed to support individualized rehabilitation sessions through coordinated interaction between therapists, patients, and the integrated rehabilitation modules. The operational workflow encompasses patient registration, rehabilitation configuration, calibration, exercise execution, performance assessment, adaptive task regulation, and longitudinal progress monitoring. This workflow enables rehabilitation activities to be tailored to individual patient capabilities while preserving continuity across multiple therapy sessions.

The platform defines two primary user roles: therapists and patients. Therapists are responsible for patient registration, rehabilitation configuration, progress monitoring, and review of rehabilitation outcomes. Patients interact directly with the rehabilitation environment through calibration procedures and rehabilitation gameplay, generating movement-performance data that are subsequently used for clinical assessment and adaptive difficulty adjustment.

### **4.3.1 Therapist Workflow**

Therapists access the platform through a dedicated clinician interface providing patient management, rehabilitation configuration, and progress monitoring functionalities.

The rehabilitation platform provides dedicated authentication interfaces for therapist login and account creation, shown in Figure 4.2. These mechanisms ensure that each therapist can securely access only the patients and rehabilitation records associated with their account.





(a) Therapist login interface used to authenticate registered users.



(b) Therapist account creation interface for registering new clinicians.

Figure 4.2: Authentication interfaces of the therapist.

After authentication, therapists are presented with a dashboard displaying the patients associated with their account, as illustrated in Figure 4.3.

When registering a new patient, the therapist creates the corresponding patient profile within the platform. The patient subsequently completes the account activation process by defining a personal password during their first authentication.





Figure 4.3: Therapist dashboard displaying the patients associated with the authenticated therapist.

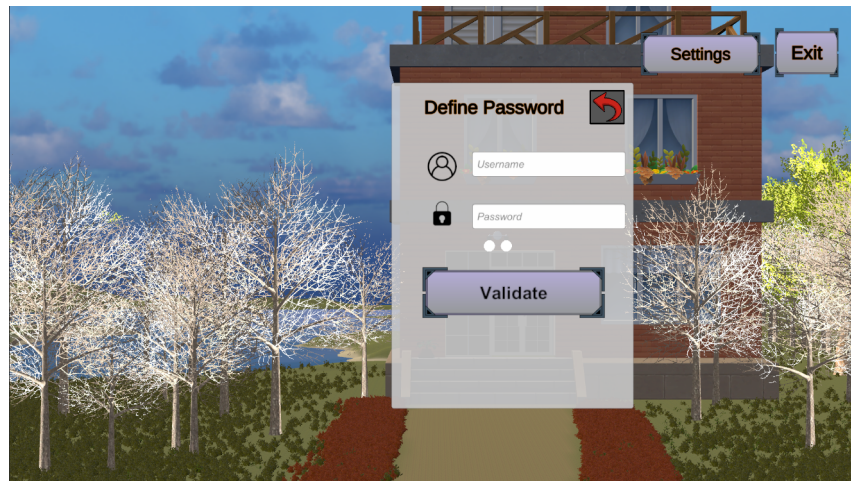
After selecting a patient, the therapist is presented with the patient management interface, shown in Figure 4.4 from which all rehabilitation-related functionalities can be accessed. Through this interface, therapists may launch any of the rehabilitation game modules to supervise a rehabilitation session, review and edit the patient's demographic information, initiate or review calibration procedures, and access rehabilitation statistics from previous sessions. The statistics interface presents gameplay performance together with the corresponding assessment metrics, enabling therapists to monitor rehabilitation progress and evaluate changes in motor performance over time.



Figure 4.4: Patient management interface providing access to rehabilitation games, calibration, rehabilitation statistics, and patient profile management.

### 4.3.2 Patient Workflow

Patients access the rehabilitation platform through individualized accounts associated with therapist-created rehabilitation profiles. During their first access, patients activate their account by defining a personal authentication password. For subsequent rehabilitation sessions, access is performed through the standard login interface shown in Figure 4.5.



(a) Patient login interface.



(b) Initial password creation during the first system access.

Figure 4.5: Authentication interfaces of the patient application.

After authentication, the platform retrieves the patient's rehabilitation profile, including the current rehabilitation progression, calibration measurements, and adaptive difficulty settings. Patients are then presented with the main rehabilitation menu shown in Figure 4.6.



Figure 4.6: Main patient menu providing access to the rehabilitation modules and calibration procedure.

From the main menu, patients may select one of the available rehabilitation game modules to begin a therapy session or initiate a calibration procedure when requested by the therapist. The rehabilitation modules resume from the patient’s previously achieved progression state, while calibration updates the individualized movement limits used to personalize subsequent rehabilitation activities.

At the end of each session, gameplay performance, assessment metrics, and rehabilitation progression are automatically stored within the patient’s profile for future sessions and therapist review.

## 4.4 The Motion Capture Layer

The motion capture layer is responsible for acquiring, processing, and distributing upper-limb movement data throughout the rehabilitation platform. It establishes the connection between patient movements and the virtual rehabilitation environment, enabling real-time interaction during rehabilitation exercises.

Movement acquisition is performed using the Microsoft Kinect v2 sensor and Kinect for Windows **SDK**, which generate three-dimensional skeletal representations of the user. The resulting skeletal coordinates are processed through a centralized motion processing pipeline that extracts rehabilitation-relevant kinematic features, including joint angles, reach distances, movement trajectories, workspace boundaries, and trunk displacement measurements.

These kinematic features are subsequently made available to the rehabilitation modules, assessment framework, and adaptive difficulty system through shared software interfaces. This centralized architecture ensures consistency of movement analysis across all platform components while supporting responsive real-time interaction throughout rehabilitation sessions.



#### 4.4.1 Kinect v2 Sensor

The Microsoft Kinect v2 sensor was selected as the motion acquisition device due to its ability to provide real-time markerless skeletal tracking while requiring no wearable sensors or markers. Compared with the 20 joints available in Kinect v1, it offers richer kinematic information for upper-limb movement assessment. The sensor offers sufficient spatial and temporal resolution for interactive upper-limb rehabilitation and can be readily integrated with Unity through the Kinect for Windows **SDK**.

The Kinect v2 sensor is mounted approximately 1.4 m above the ground and positioned approximately 1.5 m in front of the participant, as illustrated in Figure 4.7. This configuration provides reliable upper-body skeletal tracking while minimizing self-occlusion during rehabilitation exercises.

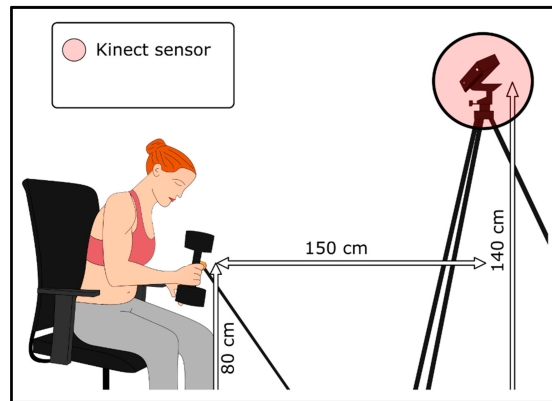


Figure 4.7: Experimental rehabilitation setup showing Kinect v2 positioning, patient interaction distance, and tracking area. Adapted from [62].

Rehabilitation exercises were designed to be performed primarily while facing the sensor, reducing tracking degradation associated with excessive body rotation or limb occlusion. No additional sensor fusion or predictive tracking algorithms were implemented, and movement acquisition relied exclusively on the skeletal tracking functionality provided by the Kinect for Windows **SDK**.

Although Kinect-based tracking does not provide the accuracy of laboratory-grade optical motion capture systems, it offers a practical compromise between measurement capability, implementation complexity, and accessibility. Given that the primary objective of the proposed platform was to support interactive rehabilitation, movement assessment, and adaptive exercise progression, the Kinect v2 provided an appropriate sensing solution for the requirements of the system.

#### 4.4.2 Kinect SDK Integration

The Kinect for Windows **SDK** was integrated into the Unity-based rehabilitation platform to provide access to Kinect v2 skeletal tracking data. For each detected user, the **SDK** estimates the **3D**

coordinates and tracking state of 25 anatomical joints, which are continuously updated throughout rehabilitation sessions.

Rather than using the raw skeletal coordinates directly within the rehabilitation modules, a centralized motion processing layer was implemented to extract rehabilitation-relevant kinematic features from the tracked joints. These features include joint angles, reach amplitude, upper-limb trajectories, workspace boundaries, and trunk displacement measurements.

The resulting kinematic information is exposed through shared software interfaces and used by the rehabilitation modules, assessment framework, and adaptive difficulty system. This centralized architecture avoids redundant computations, ensures consistency of movement analysis across platform components, and simplifies future extension of the rehabilitation framework.

Although the Kinect **SDK** provides robust real-time skeletal tracking for interactive rehabilitation applications, several technical limitations must be acknowledged. The **SDK** estimates joint positions algorithmically from depth information rather than directly measuring anatomical landmarks, meaning that skeletal coordinates represent approximations of body posture and movement. Tracking quality may additionally deteriorate during self-occlusion, overlapping limb positions, rapid motion, or partial visibility of the user within the sensor field of view.

Furthermore, because the Kinect **SDK** was originally developed for general-purpose body tracking rather than clinical biomechanical analysis, the extracted skeletal information should not be interpreted as a substitute for laboratory-grade motion capture systems or formal clinical measurement instruments. Consequently, the proposed platform utilizes Kinect-derived skeletal data primarily for interactive rehabilitation, relative movement assessment, compensation monitoring, and longitudinal performance tracking rather than precise biomechanical quantification.

#### 4.4.3 Kinect Joint Smoothing

The Kinect v2 sensor provides real-time estimates of body joint positions; however, these measurements are affected by tracking noise, depth estimation errors, and small frame-to-frame fluctuations. Such noise can produce visible jitter in the avatar representation and negatively affect movement analysis metrics that rely on trajectory derivatives, such as velocity, acceleration, and smoothness measures. To improve the stability of the tracked wrist and elbow trajectories, an adaptive smoothing approach based on the One Euro Filter was implemented.

The One Euro Filter was originally proposed by Casiez et al. [108], as a low-latency solution for interactive motion tracking systems. Unlike conventional low-pass filters that apply a fixed amount of smoothing regardless of movement speed, the One Euro Filter dynamically adjusts its cut-off frequency according to the estimated velocity of the tracked joint. This allows strong smoothing when the user is stationary while reducing lag during intentional movements.

For each incoming Kinect sample, an instantaneous velocity estimate is first computed from the current joint position and the previously filtered position:

$$\dot{\mathbf{x}}(t) = \frac{\mathbf{x}(t) - \mathbf{x}_f(t - \Delta t)}{\Delta t} \quad (4.1)$$

where  $\mathbf{x}(t)$  denotes the current joint position measurement obtained from the Kinect sensor,  $\mathbf{x}_f(t - \Delta t)$  denotes the filtered joint position from the previous frame,  $\dot{\mathbf{x}}(t)$  denotes the instantaneous velocity estimate, and  $\Delta t$  is the elapsed time since the previous sample.

The velocity estimate is subsequently smoothed using a first-order low-pass filter:

$$\dot{\mathbf{x}}_f(t) = (1 - \alpha_d)\dot{\mathbf{x}}_f(t - \Delta t) + \alpha_d\dot{\mathbf{x}}(t) \quad (4.2)$$

where  $\dot{\mathbf{x}}_f(t)$  denotes the filtered velocity estimate and the derivative filter coefficient  $\alpha_d$  is computed as

$$\alpha_d = \frac{2\pi f_d \Delta t}{2\pi f_d \Delta t + 1} \quad (4.3)$$

and  $f_d$  denotes the derivative cut-off frequency.

The magnitude of the filtered velocity is then used to determine an adaptive cut-off frequency for position smoothing:

$$f_c = f_{\min} + \beta |\dot{\mathbf{x}}_f(t)| \quad (4.4)$$

where  $f_c$  denotes the adaptive position-filter cut-off frequency at time  $t$ ,  $f_{\min}$  is the minimum cut-off frequency,  $\beta$  is the velocity-scaling coefficient that controls the responsiveness of the filter to motion, and  $|\dot{\mathbf{x}}_f(t)|$  is the Euclidean norm of the filtered velocity estimate.

When the joint is moving slowly, the cut-off frequency remains close to  $f_{\min}$ , resulting in stronger smoothing and effective suppression of Kinect jitter. During rapid movements, the cut-off frequency increases, reducing smoothing and allowing the avatar to respond more quickly to the user's motion.

The position filter coefficient is computed as

$$\alpha = \frac{2\pi f_c \Delta t}{2\pi f_c \Delta t + 1} \quad (4.5)$$

and the filtered position is updated according to

$$\mathbf{x}_f(t) = (1 - \alpha)\mathbf{x}_f(t - \Delta t) + \alpha\mathbf{x}(t) \quad (4.6)$$

where  $\mathbf{x}_f(t)$  denotes the filtered joint position.

This adaptive filtering approach was applied to both wrist and elbow joint positions before they were used by the Inverse Kinematics (**IK**) system controlling the rehabilitation avatar. Compared with traditional threshold-based smoothing approaches, the One Euro Filter provides smoother trajectories while preserving natural movement dynamics and maintaining low latency.

An additional advantage of this approach is its suitability for quantitative movement analysis. Since the filter operates as a continuous adaptive low-pass filter rather than suppressing motion through threshold or state transitions, it preserves the underlying trajectory characteristics required by smoothness metrics such as **SPARC**. Consequently, the same filtered trajectories can

be used both for avatar control and for objective assessment of movement quality across different rehabilitation games.

All subsequent kinematic analyses, including joint-angle estimation, compensation detection, and **SPARC** smoothness calculations, were performed using the filtered joint trajectories  $\mathbf{x}_f(t)$  rather than the raw Kinect measurements. This ensures that clinically relevant movement characteristics are preserved while minimising the influence of sensor noise.

#### 4.4.4 Patient Data Management and Persistence

To support longitudinal rehabilitation monitoring and adaptive exercise continuity, the platform incorporates a patient data management subsystem responsible for storing rehabilitation information across sessions.

Persistent storage enables rehabilitation sessions to resume from previously achieved progression levels while preserving individualized adaptation parameters and calibration data. This functionality is particularly important in adaptive rehabilitation environments, where exercise conditions evolve according to patient performance over time.

As illustrated in Figure 4.8, the database schema organizes information related to patient management, rehabilitation configuration, movement assessment, gameplay analytics, and progression tracking. Through the therapist interface, stored records can be reviewed to monitor rehabilitation progression and support exercise personalization.

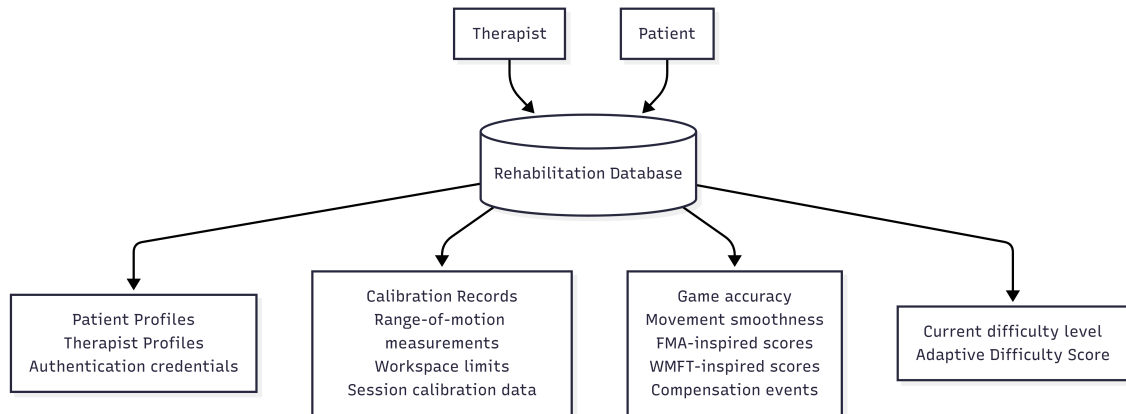


Figure 4.8: Conceptual organization of the rehabilitation platform database subsystem.

## 4.5 Rehabilitation Environment Design

The rehabilitation platform was designed around a unified virtual environment intended to provide a consistent and engaging context for rehabilitation activities. Rather than presenting rehabilitation exercises through isolated menus and game scenes, the system incorporates a common virtual world that serves as the central interaction space for both patients and therapists.

The environment is organized around a virtual house that functions as the primary navigation and management area. Within this space, users can access rehabilitation modules, review

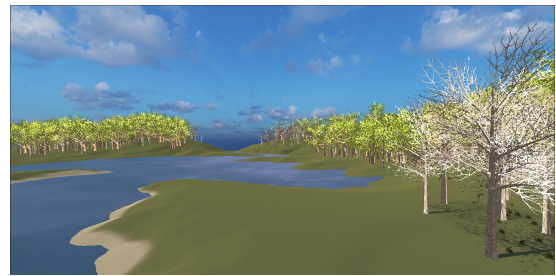
progression information, and interact with platform management functionalities. This design was adopted to provide a familiar and intuitive organizational structure while reducing the perception of interacting with separate software components.

The rehabilitation activities themselves are situated within an outdoor environment surrounding the house. The virtual setting incorporates natural elements including trees, vegetation, a river, and open landscape areas. A bright colour palette and natural scenery were intentionally selected to create a welcoming and non-clinical atmosphere, with the objective of improving user engagement and reducing the repetitive nature often associated with rehabilitation exercises.

The structure of the virtual rehabilitation environment is illustrated in Figure 4.9.



(a) Exterior view of the central virtual house used for navigation and platform management.



(b) Outdoor rehabilitation environment where therapeutic activities are performed.

Figure 4.9: Virtual rehabilitation environment developed for the platform. The central house functions as the main interaction hub, while rehabilitation activities are embedded within the surrounding outdoor environment.

Although the visual environment does not directly influence movement assessment or rehabilitation adaptation mechanisms, it was considered an important component of the overall user experience. By embedding therapeutic activities within a coherent virtual world, the platform aims to promote sustained participation and provide a more enjoyable rehabilitation experience.

## 4.6 Clinical Assessment Framework

To provide objective measures of upper-limb motor performance, the system incorporates Kinect-derived proxies of two widely used clinical assessment instruments: **FMA-UE** and the **WMFT**. These assessments were selected because they evaluate complementary aspects of post-stroke motor recovery. The **FMA-UE** primarily measures motor impairment and movement selectivity, whereas the **WMFT** focuses on functional task execution and movement efficiency.

Because several items of the original assessments require clinician observation, manual manipulation, or fine motor evaluation, only the components that could be reliably estimated from Kinect skeletal tracking were implemented. Therefore, the resulting scores should be interpreted as kinematic proxies rather than direct replacements for clinician-administered assessments.

In addition to these assessment proxies, the framework incorporates an independent movement smoothness measure based on the **SPARC** metric. Although the **FMA-UE** includes a coordination and movement-quality component, its clinical evaluation is based on observational judgement of



factors such as movement decomposition, tremor, accuracy, and execution speed during a standardized task. Rather than introducing a Kinect-specific reinterpretation of this assessment item, the proposed framework evaluates movement quality separately through the **SPARC** metric, which provides a continuous and objective kinematic measure of movement smoothness during game-play.

#### 4.6.1 Kinect-based FMA-UE Proxy

The **FMA-UE** is one of the most widely used clinical instruments for evaluating post-stroke motor impairment. However, several components were outside the scope of this work, as they require direct clinician observation, reflex testing, wrist manipulation, or fine motor assessment that cannot be reliably derived from Kinect v2 skeletal tracking.

Consequently, the proposed platform implements a Kinect-based **FMA-UE** proxy composed exclusively of assessment items that can be approximated from upper-limb kinematic data. The implemented framework focuses on proximal upper-limb function, including shoulder and elbow movements, while excluding reflex, wrist, forearm rotation, hand-related, and coordination-assessment components.

In total, 6 assessment items derived from Sections II, III, IV, and V of the **FMA-UE** were implemented, producing a maximum achievable score of 12 points. The mapping is summarised in Table 4.1. The resulting score should therefore be interpreted as a movement-performance indicator inspired by the **FMA-UE** rather than a digital reproduction of the original clinical instrument.

Table 4.1: Implemented FMA-UE proxy items and corresponding Kinect-derived kinematic variables.

| <b>FMA-UE Section</b> | <b>Assessment Item</b>                         | <b>Kinematic Variable</b>                                                         |
|-----------------------|------------------------------------------------|-----------------------------------------------------------------------------------|
| II-C                  | Shoulder Abduction                             | Peak frontal-plane shoulder abduction angle                                       |
| II-E                  | Elbow Flexion                                  | Maximum elbow flexion magnitude                                                   |
| III-B                 | Elbow Extension                                | Maximum elbow extension angle                                                     |
| IV-B                  | Shoulder Flexion (0–90°) with Elbow Extended   | Peak sagittal-plane shoulder flexion below 90° while maintaining elbow extension  |
| V-A                   | Shoulder Abduction (0–90°) with Elbow Extended | Peak frontal-plane shoulder abduction below 90° while maintaining elbow extension |
| V-B                   | Shoulder Flexion (90–180°) with Elbow Extended | Peak sagittal-plane shoulder flexion above 90° while maintaining elbow extension  |

##### 4.6.1.1 Scoring Methodology

Unlike clinician-administered **FMA-UE** assessment, which evaluates predefined movements in isolation, the proposed framework estimates movement capability opportunistically during func-

tional gameplay. This design was adopted to avoid interrupting rehabilitation activities with dedicated assessment procedures while allowing continuous monitoring of motor performance. The resulting scores therefore represent the highest movement capabilities demonstrated during task execution rather than performance during formal assessment trials.

For each assessment item, the system records the maximum (or minimum, depending on the metric) kinematic value achieved over the entire task duration. This approach reflects the inherently variable nature of functional movement, where different segments of a continuous task naturally elicit different joint configurations. For example, reaching toward the upper regions of the workspace induces shoulder flexion, while lateral movements predominantly elicit shoulder abduction.

Kinematic measurements for Items IV-B and V-A/V-B were only recorded when elbow extension exceeded  $150^\circ$ . This threshold was introduced as an implementation constraint to encourage assessment of shoulder movement under conditions of substantial elbow extension, approximating the movement requirements of the corresponding **FMA-UE** items while accommodating Kinect measurement uncertainty.

The threshold-based scoring rules for each implemented **FMA-UE** proxy item are summarized in Table 4.2.

Table 4.2: Threshold-based proxy scoring criteria for the implemented **FMA-UE** assessment items. Joint angles and endpoint displacement measurements extracted from the motion-capture system were mapped to the standard **FMA-UE** ordinal scores (0–2) using predefined kinematic thresholds derived from clinical movement requirements.

| Item  | Kinematic Feature                                             | Score 0       | Score 1                 | Score 2          |
|-------|---------------------------------------------------------------|---------------|-------------------------|------------------|
| II-C  | Shoulder abduction angle                                      | $< 45^\circ$  | $45^\circ - 89^\circ$   | $\geq 90^\circ$  |
| II-E  | Maximum elbow flexion magnitude ( $\theta_{\text{flexion}}$ ) | $< 20^\circ$  | $20^\circ - 89^\circ$   | $\geq 90^\circ$  |
| III-B | Elbow extension angle (peak extension)                        | $< 100^\circ$ | $100^\circ - 149^\circ$ | $\geq 150^\circ$ |
| IV-B  | Shoulder flexion $0-90^\circ$ (elbow extended)                | $< 20^\circ$  | $20^\circ - 74^\circ$   | $\geq 75^\circ$  |
| V-A   | Shoulder abduction $0-90^\circ$ (elbow extended)              | $< 30^\circ$  | $30^\circ - 74^\circ$   | $\geq 75^\circ$  |
| V-B   | Shoulder flexion $90-180^\circ$ (elbow extended)              | $< 90^\circ$  | $90^\circ - 149^\circ$  | $\geq 150^\circ$ |

The threshold values presented in Tables 4.2 were derived from the movement requirements described in the original **FMA-UE** protocol and adapted for implementation using Kinect-based skeletal tracking. Where the clinical assessment specifies the ability to achieve or maintain particular movement patterns rather than exact quantitative angular values, corresponding kinematic thresholds were defined using literature-reported upper-limb ranges of motion and iterative testing within the rehabilitation environment. The selected thresholds were intended to provide clinically

meaningful separation between absent, partial, and near-complete movement performance while maintaining robustness to Kinect measurement variability. Consequently, the proposed thresholds should be interpreted as engineering approximations of the original clinical scoring criteria rather than validated clinical cut-off values.

#### 4.6.1.2 Final Score Computation and Compensation Strategy

Upon completion of a task or level, raw item scores are computed by mapping the recorded peak kinematic values to predefined threshold-based grading rules derived from the clinical **FMA-UE** scale.

The final normalized score is computed as:

$$\text{NormalisedScore} = \text{Clamp}_{[0,1]} \left( \frac{\text{TotalFMA}}{12} \cdot (1 - 0.25 \cdot C_{\text{index}}) \right) \quad (4.7)$$

A trunk compensation penalty based on the Compensation Index,  $C_{\text{index}}$ , defined in Subsection 4.6.5 was applied to the final score.

The compensation penalty was introduced as a behavioural weighting factor intended to discourage excessive reliance on compensatory strategies without allowing compensation measures to dominate the impairment-related score. A maximum penalty of 25% was selected to ensure that movement quality influenced the final assessment while preserving the primary contribution of motor performance measures. The value should therefore be interpreted as an implementation parameter rather than a clinically validated weighting coefficient.

#### 4.6.2 WMFT Proxy Assessment

The **WMFT** is a widely used clinical assessment for evaluating upper-limb motor function following neurological injury. The original **WMFT** consists of timed functional tasks scored using a clinician-observed **FAS**, which assesses movement quality on an ordinal scale from 0 to 5.

Several **WMFT** tasks require measurements that cannot be reliably obtained using a single Kinect v2 sensor, including grip strength, object manipulation, and fine finger movements. Consequently, the present work implements a Kinect-based **WMFT** proxy framework that estimates performance using upper-limb kinematic features extracted from skeletal tracking data. The resulting scores should therefore be interpreted as rehabilitation decision-support metrics rather than direct clinical **WMFT** scores.

##### 4.6.2.1 WMFT Items Assessed

6 **WMFT** tasks were selected because their primary movement requirements can be approximated using Kinect-derived kinematic measurements. Table 4.3 summarises the assessed items and their corresponding kinematic proxies.

Table 4.3: WMFT tasks included in the Kinect-based proxy assessment.

| WMFT Item | Clinical Task      | Kinematic Proxy                          |
|-----------|--------------------|------------------------------------------|
| WMFT-01   | Forearm to Table   | Peak shoulder abduction angle            |
| WMFT-02   | Forearm to Box     | Peak wrist height above baseline         |
| WMFT-03   | Extend Elbow       | Peak elbow extension angle               |
| WMFT-05   | Hand to Table      | Peak shoulder flexion angle              |
| WMFT-06   | Hand to Box        | Peak shoulder flexion angle (high phase) |
| WMFT-08   | Reach and Retrieve | Peak forward wrist displacement          |

#### 4.6.2.2 Kinematic Feature Extraction

During task execution, Kinect joint positions are continuously tracked and smoothed using the One Euro Filter described in Section 4.4.3.

From these smoothed positions, two foundational directional vectors are recomputed every frame: the trunk reference axis, defined by the vector from SpineBase to SpineShoulder, and the upper arm vector, defined by the vector from Shoulder to Elbow; the corresponding joints are illustrated in Figure 2.1b. To isolate specific anatomical movements, these vectors are projected onto distinct 2D planes:

**Sagittal Plane (Forward/Backward):** Vectors are projected onto the YZ plane to compute shoulder flexion angles.

**Frontal Plane (Lateral):** Vectors are projected onto the XY plane to compute shoulder abduction angles.

Prior to task execution, a resting baseline is established by averaging 20 consecutive Kinect frames:

$$\bar{\mathbf{p}}_{\text{baseline}} = \frac{1}{20} \sum_{i=1}^{20} \mathbf{p}_i \quad (4.8)$$

where  $\mathbf{p}_i \in \mathbb{R}^3$  denotes the three-dimensional position of the monitored joint in frame  $i$ , and  $\bar{\mathbf{p}}_{\text{baseline}}$  represents the corresponding average resting joint position. Baseline wrist and spine positions are subsequently used as reference points for displacement-based performance metrics.

The following kinematic features are extracted and their peak values retained for scoring.

**Shoulder Flexion** Shoulder flexion is computed in the sagittal plane using the angle between the torso vector  $\mathbf{T}$  and the upper-arm vector  $\mathbf{u}$ :

$$\theta_{\text{flex}} = \angle(\text{proj}_{yz}(\mathbf{T}), \text{proj}_{yz}(\mathbf{u})) \quad (4.9)$$

Only the magnitude of the projected angle was retained for scoring.

**Shoulder Abduction** Shoulder abduction is calculated in the frontal plane:

$$\theta_{\text{abd}} = \angle(\text{proj}_{xy}(\mathbf{T}), \text{proj}_{xy}(\mathbf{u})) \quad (4.10)$$

**Elbow Extension** The elbow extension angle is calculated as the interior angle formed by the shoulder, elbow, and wrist joints:

$$\theta_{\text{ext}} = \angle(\mathbf{s} - \mathbf{e}, \mathbf{w} - \mathbf{e}) \quad (4.11)$$

where  $\mathbf{s}$ ,  $\mathbf{e}$ , and  $\mathbf{w}$  represent the filtered shoulder, elbow, and wrist positions, respectively.

**Forward Reach Distance** To reduce the influence of compensatory trunk movements, wrist displacement is corrected using the measured displacement of the spine base:

$$d_{\text{reach}} = \max(0, (w_z - \bar{w}_z) - (s_z - \bar{s}_z)) \quad (4.12)$$

where  $w_z$  and  $s_z$  denote the current wrist and spine-base positions along the depth axis, while  $\bar{w}_z$  and  $\bar{s}_z$  represent the corresponding baseline positions measured prior to task execution. The resulting metric provides an estimate of forward upper-limb reaching performance while partially compensating for anterior trunk displacement. Consequently, the measure should be interpreted as a trunk-corrected reach-distance proxy rather than a direct measure of isolated arm movement.

**Wrist Height** Vertical wrist displacement relative to baseline is computed as

$$h_{\text{wrist}} = \max(0, w_y - \bar{w}_y). \quad (4.13)$$

where:

- $h_{\text{wrist}}$  is the wrist elevation above the reference position (m);
- $w_y$  is the instantaneous vertical coordinate of the wrist joint in the global reference frame (m);
- $\bar{w}_y$  is the baseline vertical wrist coordinate measured during the initial neutral posture (m);
- $\max(0, \cdot)$  ensures that only upward displacement is considered, assigning a value of zero when the wrist is below its baseline height.

#### 4.6.2.3 Functional Ability Scale Mapping

Each kinematic feature is mapped to a proxy **FAS** score ranging from 0 to 5 using task-specific thresholds:

$$\text{FAS}(x) = \begin{cases} 5, & x \geq \tau_5 \\ 4, & \tau_4 \leq x < \tau_5 \\ 3, & \tau_3 \leq x < \tau_4 \\ 2, & \tau_2 \leq x < \tau_3 \\ 1, & \tau_1 \leq x < \tau_2 \\ 0, & x < \tau_1 \end{cases} \quad (4.14)$$

where  $x$  denotes the measured kinematic feature and  $\tau_1, \dots, \tau_5$  are task-specific thresholds. A score of 0 corresponds to movement that does not exceed the minimum detection threshold  $\tau_1$ , representing the absence of a meaningful task attempt within the proxy framework.

Consistent with the original **WMFT** definition, a score of two indicates that the movement was completed but exhibited severe abnormality, difficulty, or compensatory behaviour. It does not indicate task failure.

The threshold values presented in Table 4.4 were selected to provide a kinematic approximation of the ordinal scoring structure of the **WMFT FAS**. In the original clinical assessment, **FAS** ratings are assigned by trained clinicians based on qualitative observations of movement quality, task completion, coordination, and functional performance. Because these characteristics cannot be fully captured using Kinect v2 skeletal tracking alone, the proposed framework estimates functional ability using objectively measurable kinematic features extracted during task execution.

Table 4.4: Threshold values used to assign proxy FAS scores.

| Item    | $\tau_1$ | $\tau_2$ | $\tau_3$ | $\tau_4$ | $\tau_5$ | Unit |
|---------|----------|----------|----------|----------|----------|------|
| WMFT-01 | 3        | 8        | 15       | 22       | 30       | °    |
| WMFT-02 | 0.03     | 0.08     | 0.14     | 0.19     | 0.24     | m    |
| WMFT-03 | 10       | 60       | 100      | 140      | 160      | °    |
| WMFT-05 | 5        | 15       | 28       | 38       | 50       | °    |
| WMFT-06 | 5        | 30       | 55       | 75       | 90       | °    |
| WMFT-08 | 0.05     | 0.10     | 0.18     | 0.24     | 0.30     | m    |

The threshold values were selected based on **WMFT** task requirements, upper-limb kinematic ranges reported in the rehabilitation literature, and iterative testing within the proposed rehabilitation environment.

Formal clinical validation against therapist-administered **WMFT** assessments was outside the scope of the present work. Therefore, the proposed thresholds should be regarded as engineering approximations intended for within-system performance monitoring and longitudinal tracking of rehabilitation progress rather than clinically validated diagnostic criteria.

#### 4.6.2.4 Normalized Task Performance Score

In addition to the kinematic **FAS** estimate, task duration is incorporated through a normalised time score:

$$\tilde{t}_i = \begin{cases} 0, & \text{if the task timed out,} \\ \text{clip}\left(1 - \frac{t_i}{T_{\max}}, 0, 1\right), & \text{otherwise.} \end{cases} \quad (4.15)$$

where  $t_i$  denotes the task completion time and  $T_{\max} = 120\text{s}$  corresponds to the maximum time allowed in the **WMFT**. This normalization does not form part of the original **WMFT** scoring procedure but is introduced to express task duration on a bounded  $[0, 1]$  scale, enabling its integration with the kinematic performance metrics used by the adaptive algorithm.

The final score for each **WMFT** proxy item is computed as

$$S_i = 0.60 \left( \frac{\text{FAS}_i}{5} \right) + 0.40 \tilde{t}_i \quad (4.16)$$

The weighting was empirically chosen to emphasize movement quality (**FAS** proxy) over execution speed while still retaining temporal performance information.

#### 4.6.2.5 Session Score

A single session-level **WMFT** proxy score is calculated by averaging all assessed item scores:

$$\bar{S}_{\text{WMFT}} = \frac{1}{N} \sum_{i=1}^N S_i \quad (4.17)$$

where  $N$  denotes the number of **WMFT** proxy items included in the assessment ( $N = 6$  in the present implementation).

For user-facing feedback, a percentage performance score is additionally computed:

$$P = 100 \left( 0.60, \bar{\text{FAS}}_{\text{norm}} + 0.40, \bar{\tilde{t}} \right) \quad (4.18)$$

where

$$\bar{\text{FAS}}_{\text{norm}} = \frac{1}{N} \sum_{i=1}^N \frac{\text{FAS}_i}{5} \quad (4.19)$$

and

$$\bar{\tilde{t}} = \frac{1}{N} \sum_{i=1}^N \tilde{t}_i. \quad (4.20)$$

where  $\text{FAS}_i/5$  normalizes the **FAS** score to the interval  $[0, 1]$ , ensuring compatibility with the normalized completion-time metric  $\tilde{t}_i$  and allowing both components to contribute proportionally to the overall performance score.

The resulting **WMFT** proxy score is subsequently incorporated into the composite rehabilitation score described in Subsection 4.7.2.

#### 4.6.3 Movement Smoothness Assessment

To quantify movement smoothness during gameplay, the proposed platform implements the **SPARC** metric, originally introduced by Balasubramanian et al. [71].

The computation is based on the **3D** wrist trajectory obtained from Kinect v2 skeletal tracking. During task execution, wrist positions are continuously recorded in Kinect camera coordinates and converted into a scalar speed profile by computing the magnitude of the **3D** velocity vector:

$$v(t) = \left\| \frac{d\mathbf{x}(t)}{dt} \right\| = \sqrt{\dot{x}^2 + \dot{y}^2 + \dot{z}^2} \quad (4.21)$$

where  $v(t)$  denotes the instantaneous wrist speed at time  $t$ ,  $\mathbf{x}(t) = [x(t), y(t), z(t)]^T$  represents the three-dimensional wrist position vector, and  $\dot{x}$ ,  $\dot{y}$ , and  $\dot{z}$  denote the corresponding velocity components along the Kinect  $x$ -,  $y$ -, and  $z$ -axes. The use of a full **3D** trajectory preserves depth-related reaching movements that would be lost if analysis were restricted to a two-dimensional projection.

Because Kinect samples are acquired at non-uniform frame intervals, the recorded trajectory is first resampled onto a uniformly spaced temporal grid using linear interpolation. A discrete speed profile is subsequently computed and transformed into the frequency domain using a one-sided Discrete Fourier Transform (**DFT**).

Following the original **SPARC** formulation, the magnitude spectrum is normalised using the Direct Current (**DC**) spectral component:

$$\hat{V}(f) = \frac{|V(f)|}{|V(0)|} \quad (4.22)$$

where  $V(f)$  denotes the Fourier transform of the wrist speed profile,  $|V(f)|$  is its magnitude spectrum, and  $V(0)$  represents the zero-frequency (**DC**) component of the spectrum. The **DC** component corresponds to the mean value of the speed signal and is used as a normalisation factor to make the spectral representation independent of the overall movement amplitude.

In its original formulation, **SPARC** is defined as the negative arc length of the normalised velocity spectrum. Since Kinect measurements are acquired as discrete time samples, the proposed implementation approximates this formulation using a discrete summation over frequency bins:

$$\text{SPARC} = - \sum_{k=1}^{f_{c,\text{bin}}} \sqrt{\left(\frac{1}{f_{c,\text{bin}}}\right)^2 + (\hat{V}[k] - \hat{V}[k-1])^2} \quad (4.23)$$

where  $\hat{V}[k]$  denotes the normalised magnitude spectrum at frequency bin  $k$ , and  $f_{c,\text{bin}}$  represents the index of the cutoff frequency bin corresponding to the selected cutoff frequency  $f_c$ .



Less negative values indicate smoother movement. Smooth, coordinated trajectories exhibit compact low-frequency spectra and therefore produce **SPARC** values closer to zero, whereas fragmented movements containing multiple corrective sub-movements generate broader spectra and more negative **SPARC** values.

To facilitate integration with the rehabilitation game and subsequent scoring procedures, the raw **SPARC** value is linearly normalised to the interval  $[0, 1]$ , where 0 represents highly fragmented movement and 1 represents smooth, continuous motion.

The resulting smoothness estimate is used both as an independent performance metric and as the basis for the movement-quality assessment incorporated within the **FMA-UE** proxy framework.

#### 4.6.4 Compensatory Movement Detection

Compensatory trunk and shoulder movements were monitored throughout each rehabilitation task using Kinect skeletal tracking data. Three compensation indicators were computed from the tracked joint positions:

- Forward trunk lean
- Lateral trunk lean
- Shoulder elevation

To reduce sensor noise, all joint positions were first smoothed using the filtering pipeline described in Section 4.4.3. Let

$$\mathbf{v}_{spine} = \mathbf{p}_{SpineShoulder} - \mathbf{p}_{SpineBase}$$

where  $\mathbf{p}_{SpineShoulder} = [x_{SS}, y_{SS}, z_{SS}]^T$  and  $\mathbf{p}_{SpineBase} = [x_{SB}, y_{SB}, z_{SB}]^T$  are the 3D coordinates of the SpineShoulder and SpineBase joints, respectively.

##### 4.6.4.1 Baseline Calibration

To account for inter-subject variability in resting posture, anthropometric differences, and potential pathological asymmetries (e.g., trunk inclination or shoulder subluxation), a session-specific baseline calibration was performed prior to each task.

Over  $N = 20$  consecutive frames, baseline estimates of trunk and shoulder-related measures were computed as mean values of the raw signals:

$$\bar{\theta}_{forward,0}, \quad \bar{\theta}_{lateral,0}, \quad \bar{d}_{elev,0}.$$

where  $\bar{\theta}_{forward,0}$  denotes the baseline forward trunk lean angle,  $\bar{\theta}_{lateral,0}$  denotes the baseline lateral trunk lean angle, and  $\bar{d}_{elev,0}$  denotes the baseline shoulder elevation distance measured during the initial resting calibration period.

All compensation metrics are therefore expressed relative to this baseline, enabling a normalized within-subject representation of compensatory movement.

#### 4.6.4.2 Forward Trunk Lean

Forward trunk lean was computed by projecting the trunk vector onto the sagittal plane:

$$\mathbf{v}_{sag} = (0, v_y, v_z).$$

where  $\mathbf{v}_{sag}$  denotes the sagittal-plane projection of the trunk vector  $\mathbf{v}_{spine}$ , and  $v_y$  and  $v_z$  are the vertical and depth components of  $\mathbf{v}_{spine}$ , respectively.

The raw trunk inclination angle was defined as:

$$\theta_{forward}^{raw} = \cos^{-1} \left( \frac{\mathbf{v}_{sag} \cdot \mathbf{u}}{\|\mathbf{v}_{sag}\|} \right), \quad \mathbf{u} = (0, 1, 0).$$

where  $\theta_{forward}^{raw}$  is the uncorrected forward trunk lean angle,  $\mathbf{u}$  is the vertical unit vector,  $\mathbf{v}_{sag} \cdot \mathbf{u}$  denotes the dot product between the projected trunk vector and the vertical axis, and  $\|\mathbf{v}_{sag}\|$  is the Euclidean norm of the projected trunk vector.

Baseline correction was then applied:

$$\theta_{forward} = \max(0, \theta_{forward}^{raw} - \bar{\theta}_{forward,0}).$$

where  $\bar{\theta}_{forward,0}$  denotes the baseline forward trunk lean angle obtained during the calibration period, and  $\theta_{forward}$  represents the baseline-corrected forward trunk lean used for compensatory movement detection. This formulation isolates task-evoked forward trunk displacement relative to the participant's calibrated resting posture.

#### 4.6.4.3 Lateral Trunk Lean

Lateral trunk lean was computed analogously by projecting the trunk vector onto the frontal plane:

$$\mathbf{v}_{front} = (v_x, v_y, 0).$$

The raw lateral inclination angle was defined as:

$$\theta_{lateral}^{raw} = \cos^{-1} \left( \frac{\mathbf{v}_{front} \cdot \mathbf{u}}{\|\mathbf{v}_{front}\|} \right), \quad \mathbf{u} = (0, 1, 0).$$

Baseline correction was applied as:

$$\theta_{lateral} = \max(0, \theta_{lateral}^{raw} - \bar{\theta}_{lateral,0}).$$

Higher values indicate increased lateral trunk displacement relative to baseline posture.

#### 4.6.4.4 Shoulder Elevation

Shoulder elevation was defined as the vertical displacement between the affected shoulder joint and the SpineShoulder joint:

$$d_{elev}^{raw} = (y_{shoulder} - y_{spineShoulder}) \times 100,$$

where Kinect v2 joint coordinates are expressed in metres, and the scaling factor converts the measurement to centimetres for interpretability.

Baseline correction was applied to account for resting asymmetries:

$$d_{elev} = \max(0, d_{elev}^{raw} - \bar{d}_{elev,0}).$$

This measure serves as a proxy for compensatory shoulder elevation strategies commonly associated with reduced proximal stability during upper-limb reaching tasks.

#### 4.6.5 Compensation Index

The three compensation measures were normalised relative to rehabilitation-inspired thresholds:

$$F = \frac{\theta_{forward}}{30^\circ},$$

$$L = \frac{\theta_{lateral}}{25^\circ},$$

$$S = \frac{d_{elev}}{40},$$

where  $d_{elev}$  represents shoulder elevation expressed in centimetres.

The overall Compensation Index (CI) was computed as

$$CI = \text{Clamp}_{[0,1]}(0.40F + 0.35L + 0.25S).$$

The output was constrained to the interval  $[0, 1]$ , where 0 indicates no detectable compensation and 1 indicates severe compensation.

A feedback activation threshold ( $C_{\text{index}} \geq 0.35$ ) was selected empirically during system development to balance sensitivity and specificity of feedback generation. Lower thresholds resulted in frequent warnings during acceptable movement variability, whereas higher thresholds reduced the responsiveness of the compensation monitoring system. Consequently, the selected threshold should be regarded as an engineering design parameter intended to support rehabilitation interaction rather than a clinically established compensation criterion.

## 4.7 Adaptive Rehabilitation Framework

The proposed rehabilitation system employs a **DDA** framework that continuously adapts task difficulty according to the patient's motor performance. The objective is to maintain an optimal challenge level throughout therapy, preventing both frustration caused by excessive difficulty and disengagement caused by tasks that are too easy. Difficulty is represented by a continuous variable  $d \in [0, 1]$ , where  $d = 0$  corresponds to the easiest configuration and  $d = 1$  corresponds to the most demanding configuration within the system.

At the beginning of each task, all adjustable game parameters are derived from the current difficulty value using linear interpolation between predefined minimum and maximum parameter values.

### 4.7.1 Performance Metrics

Patient performance is evaluated after every task using four complementary metrics designed to capture both clinical motor function and task-specific execution quality.

#### 4.7.1.1 FMA-UE Score

The **FMA-UE** score is computed from movement-quality indicators extracted from the Kinect v2 skeletal data during gameplay. These indicators are combined according to the computational **FMA-UE** assessment described in Section 4.6.1, providing an objective estimate of upper-limb motor impairment. The resulting score is normalised to the interval  $[0, 1]$ , where higher values indicate movement patterns that more closely resemble normal motor function.

#### 4.7.1.2 WMFT Score

The **WMFT** score is computed from the upper-limb kinematic data captured by the Kinect v2 during gameplay. The recorded movement characteristics are processed according to the computational **WMFT** assessment described in Section 4.6.2, providing an objective estimate of functional motor performance during task execution. The resulting score is normalised to the interval  $[0, 1]$ , where higher values indicate better functional performance.

#### 4.7.1.3 Task Accuracy

Accuracy measures the extent to which the patient successfully performs the required task actions. This metric reflects the patient's ability to achieve the intended rehabilitation objectives and is normalised between 0 and 1.

#### 4.7.1.4 Movement Smoothness

Movement smoothness is assessed from the **3D** wrist trajectory captured by the Kinect v2 during gameplay. The recorded wrist positions are used to compute the **SPARC** metric, which quantifies

the smoothness of the executed movement. Smoothness is associated with motor control quality and movement coordination. The resulting value is normalized to the interval [0,1], where higher values correspond to smoother movements. Detailed computation of the **SPARC** metric is presented in Section 4.6.3.

#### 4.7.2 Composite Performance Score

To satisfy both real-time adaptation requirements and clinical reporting needs, two separate composite scores are calculated from the four performance metrics.

##### 4.7.2.1 Dynamic Difficulty Adjustment (DDA) Composite Score

The **DDA** composite score is used exclusively by the adaptive difficulty algorithm. It emphasises metrics that respond rapidly to changes in task difficulty, allowing the system to adapt efficiently between consecutive tasks.

$$DDA_{\text{comp}} = 0.45 \textit{Accuracy} + 0.25 \textit{Smoothness} + 0.15 \textit{FMA} + 0.15 \textit{WMFT} \quad (4.24)$$

Accuracy and smoothness receive higher weighting because they are directly influenced by changes in task parameters and therefore provide immediate feedback regarding the appropriateness of the current difficulty level. In contrast, Fugl-Meyer Assessment (**FMA**) and **WMFT** scores typically exhibit greater stability within a single therapy session and primarily serve as contextual indicators of motor ability.

##### 4.7.2.2 Clinical Composite Score

A second composite score is calculated for long-term clinical monitoring and therapist review.

$$\textit{Clinical}_{\text{comp}} = 0.40 \textit{FMA} + 0.40 \textit{WMFT} + 0.15 \textit{Accuracy} + 0.05 \textit{Smoothness} \quad (4.25)$$

This weighting scheme prioritises the **FMA** and **WMFT** proxy measures, as these are intended to reflect established clinical assessments of upper-limb motor recovery. Consequently, they contribute the largest proportion of the overall score. Accuracy and smoothness are included with lower weights because they are more susceptible to variation arising from game design and difficulty settings rather than underlying motor impairment alone.

The separation of adaptation and clinical evaluation scores ensures that the rehabilitation system remains responsive during therapy while preserving the clinical validity of progress reports.

### 4.7.3 Design Rationale

Several design decisions were made to balance rehabilitation effectiveness, clinical relevance, and real-time adaptability.

#### 4.7.3.1 Use of Two Composite Scores

A single composite score was found to be unsuitable for both adaptive difficulty control and clinical outcome reporting because these objectives require different performance characteristics. Difficulty adaptation requires a metric that responds rapidly to changes in task parameters, whereas clinical reporting requires a metric that reflects underlying motor recovery rather than short-term task performance.

For this reason, two separate composite scores were defined. The **DDA** composite prioritises task-sensitive metrics such as accuracy and movement smoothness, allowing the system to react quickly when a task becomes too easy or too difficult. In contrast, the clinical composite places greater emphasis on **FMA** and **WMFT** scores, which represent established measures of motor impairment and functional ability.

This separation ensures that adaptation decisions remain responsive while clinical reporting remains meaningful and comparable across sessions.

#### 4.7.3.2 Metric Weight Selection

The weighting values used in both composite scores were selected according to the expected responsiveness and clinical significance of each metric.

Accuracy and smoothness receive higher weights within the **DDA** composite because these measures change immediately when task difficulty is modified. For example, increasing target size or extending task completion time generally improves accuracy and movement quality within the same session.

Conversely, **FMA** and **WMFT** scores are expected to remain relatively stable during a single therapy session. These measures therefore serve primarily as indicators of baseline motor ability rather than immediate adaptation signals.

For clinical reporting, the weighting distribution is reversed. **FMA** and **WMFT** dominate the clinical composite because they are validated clinical outcome measures commonly used in stroke rehabilitation research, whereas accuracy and smoothness are included only as supplementary indicators of task performance.

#### 4.7.3.3 Asymmetric Difficulty Adaptation

The adaptive framework employs larger downward adjustments than upward adjustments. Specifically, the base decrease step is greater than the base increase step and failure streak amplification grows more rapidly than success streak amplification.

This asymmetry was introduced to prioritise patient safety and engagement. Excessively difficult tasks may lead to frustration, fatigue, compensatory movement patterns, and reduced motivation. In contrast, tasks that are temporarily too easy generally present a lower clinical risk. Consequently, the framework is designed to reduce difficulty rapidly when sustained struggle is detected while increasing difficulty more gradually following successful performance.

#### 4.7.3.4 Streak-Based Adaptation

To improve the stability of the adaptive controller, consecutive task outcomes are aggregated using two independent counters: a success streak,  $\text{streak}_{good}$ , and a failure streak,  $\text{streak}_{bad}$ . These variables capture short-term temporal trends in performance, allowing the system to differentiate isolated fluctuations from sustained changes in ability.

Each task outcome updates only one streak variable while resetting the other, ensuring that success and failure trends remain mutually exclusive:

$$\text{streak}_{good} \leftarrow \min(\text{streak}_{good} + 1, 5), \quad \text{streak}_{bad} \leftarrow 0,$$

for successful performance above the adaptation threshold, and

$$\text{streak}_{bad} \leftarrow \min(\text{streak}_{bad} + 1, 5), \quad \text{streak}_{good} \leftarrow 0,$$

for unsuccessful or sub-threshold performance.

The adaptive difficulty level  $D \in [0, 1]$  is then updated according to the current streak magnitude:

$$D \leftarrow \text{Clamp}_{[0,1]}(D + s_{up}(1 + 0.10 \cdot \text{streak}_{good})),$$

for successful outcomes, and

$$D \leftarrow \text{Clamp}_{[0,1]}(D - s_{down}(1 + 0.15 \cdot \text{streak}_{bad})),$$

for unsuccessful outcomes, where  $s_{up}$  and  $s_{down}$  denote the base step sizes for upward and downward adaptation respectively.

Both streak variables are bounded at a maximum value of 5, limiting the amplification factor to  $1.5\times$  for sustained success and  $1.75\times$  for sustained failure. This prevents excessive oscillations in difficulty while still allowing the system to respond more strongly to persistent performance trends compared to isolated task outcomes.

The downward adaptation rate is intentionally larger than the upward adaptation rate. This design choice reflects rehabilitation practice, where avoiding excessive challenge and patient frustration is generally more important than rapidly increasing task difficulty.

The streak-based mechanism was introduced as a lightweight temporal smoothing strategy for the adaptive controller. Compared to single-trial updates, this formulation reduces sensitivity to

stochastic performance fluctuations while preserving responsiveness to sustained trends in user performance.

More complex approaches such as reinforcement learning or probabilistic state estimation were considered less suitable due to the requirement for deterministic, real-time operation and interpretability in a clinical rehabilitation context. The proposed bounded gain scheduling ensures stable adaptation behaviour while maintaining transparent and predictable system dynamics, which is critical for clinical acceptance and therapist trust.

#### 4.7.4 Difficulty Adjustment Logic

At the completion of each task, the system determines whether the current difficulty should be increased or decreased.

A task is considered successful only when all predefined completion criteria are satisfied:

$$\text{Passed} = (\text{Accuracy} \geq 0.60) \wedge (FMA \geq 0.40) \wedge (WMFT \geq 0.40) \wedge \text{Timeout} = \text{False} \quad (4.26)$$

Difficulty is increased only when the level is successfully completed and the **DDA** composite score exceeds a predefined threshold:

$$\text{Increase Difficulty} = \text{Passed} \wedge (\text{DDA}_{\text{comp}} \geq T_r) \quad (4.27)$$

where  $T_r$  denotes the raise threshold and  $\text{DDA}_{\text{comp}}$  represents the **DDA** composite score, presented in Section 4.7.2.1.

When the completion criteria defined in Equation (4.26) are not satisfied, the difficulty level is decreased.

Following each evaluation cycle, the updated difficulty value is stored and used to configure the next rehabilitation task. This process creates a closed-loop adaptive system that continuously personalises task demands according to the patient's demonstrated performance.

## 4.8 Rehabilitation Game Framework

The rehabilitation platform comprises four therapeutic game modules designed to support upper-limb recovery through task-oriented movement practice. While each module addresses different therapeutic goals, all share a common framework responsible for workspace calibration, movement analysis, clinical assessment, compensation monitoring, adaptive difficulty adjustment, and performance logging.

Table 4.5 summarizes the primary rehabilitation objectives and characteristics of each game module. Although the games share a common underlying assessment and monitoring framework, they differ in the motor and cognitive demands imposed on the patient.



Table 4.5: Primary motor and cognitive rehabilitation focus of each game module.

| Game             | Primary Motor Focus                                                                                                                   | Primary Cognitive Processes                                                                | Task Progression           |
|------------------|---------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------|----------------------------|
| Clean the Window | Continuous upper-limb reaching, trajectory tracking, movement precision, and sustained motor execution across the reachable workspace | Sustained attention and visuomotor monitoring                                              | Time-limited               |
| Catch the Object | Goal-directed reaching, movement initiation, object interception, and rapid arm repositioning                                         | Visuomotor integration, reaction speed, and selective attention                            | Time-limited               |
| Capsule Sorting  | Reaching, object transport, spatial repositioning, and coordinated upper-limb movement sequencing                                     | Colour discrimination, decision-making, divided attention, and cognitive-motor integration | Completion-based           |
| Imitation Game   | Controlled execution of prescribed therapeutic movements, posture reproduction, and movement quality refinement                       | Motor planning, observational learning, movement recall, and sensorimotor integration      | Therapist-defined duration |

### 4.8.1 Shared System Components

#### 4.8.1.1 Patient Calibration and Range-of-Motion Assessment

During the patient's first access to the rehabilitation platform, or whenever recalibration is clinically required by the therapist, the system performs a patient-specific calibration procedure to estimate functional upper-limb movement capabilities and establish individualized interaction boundaries for rehabilitation exercises. Because motor impairment following stroke varies substantially across patients and evolves throughout the rehabilitation process, recalibration may be performed at any stage of treatment to update movement limits and maintain appropriate exercise personalization.

By adapting rehabilitation tasks according to the patient's available range of motion, the system aims to maintain achievable interaction conditions while still encouraging active movement participation and progressive motor challenge.

The calibration process is guided through a virtual instructor avatar integrated within the rehabilitation environment. For each evaluated movement, the avatar first demonstrates the target

action, after which the patient is instructed to reproduce the movement as accurately as possible, visible in Figure 4.10. This imitation-based approach was adopted to standardize movement instruction across rehabilitation sessions while reducing dependence on continuous therapist demonstration during system operation.



Figure 4.10: Calibration posture adopted by the patient before the rehabilitation session. During this stage, the system verifies correct body alignment and establishes the reference posture used for subsequent movement analysis.

Calibration may be configured to target the affected limb only or both upper limbs, according to the patient's clinical presentation. When bilateral calibration is performed, the system derives the active interaction boundaries as the conservative minimum across both sides, ensuring that rehabilitation targets remain reachable regardless of which limb is engaged during a given exercise.

The rehabilitation environment adopts a third-person interaction perspective in which patients observe a virtual avatar from behind while controlling its upper-limb movements through Kinect-based skeletal tracking. The patient and instructor avatars were based on the same underlying humanoid model to ensure visual consistency between movement demonstration and task execution. Male and female variants were available, with the appropriate model selected according to the participant's sex. The two avatars were further distinguished through their spatial positioning and interaction perspective within the rehabilitation environment. During gameplay, patients observe the controlled avatar from a posterior third-person perspective, promoting intuitive correspondence between physical and virtual arm movements. In contrast, the instructor avatar is positioned facing the patient during calibration and guided exercises in order to facilitate visual imitation of demonstrated movements. To further simplify imitation, demonstrations are presented using a mirrored perspective, allowing patients to reproduce movements as though observing themselves in a mirror.

This distinction was adopted to maintain consistency of skeletal mapping and animation behaviour throughout the platform while preserving clear functional separation between avatar roles

during rehabilitation interaction.

Although repeated calibration trials could potentially improve measurement reliability through averaging or outlier reduction, requiring multiple maximal movement repetitions may introduce additional physical strain and discomfort, particularly for patients with limited motor endurance or severe impairment. For this reason, the proposed framework prioritized practical rehabilitation usability and reduced patient burden over high-precision range-of-motion quantification.

The calibration protocol evaluates a set of upper-limb movements associated with shoulder, elbow, and wrist mobilization, as summarized in Table 4.6. These movements were selected to estimate the patient's reachable workspace, upper-limb mobility limitations, and distal movement capabilities relevant to the rehabilitation activities implemented throughout the platform.

Table 4.6: Upper-limb movements evaluated during the patient calibration procedure.

| <b>Movement</b>                         | <b>Primary Joint</b> | <b>Rehabilitation Purpose</b>                                                                                        |
|-----------------------------------------|----------------------|----------------------------------------------------------------------------------------------------------------------|
| Shoulder Abduction (Coronal Plane)      | Shoulder             | Assessment of lateral arm elevation and estimation of available shoulder abduction range of motion.                  |
| Shoulder Flexion (Sagittal Plane)       | Shoulder             | Evaluation of forward reaching capability and estimation of functional vertical workspace.                           |
| Cross-Body Reach (Horizontal Adduction) | Shoulder             | Assessment of horizontal reaching ability, midline crossing, and upper-limb coordination during cross-body movement. |
| Elbow Flexion                           | Elbow                | Evaluation of forearm mobilization, functional elbow range of motion, and proximal-distal coordination.              |
| Wrist Extension*                        | Wrist                | Guided assessment of upward wrist mobility and distal motor control.                                                 |
| Wrist Flexion*                          | Wrist                | Guided assessment of downward wrist mobility and controlled wrist articulation.                                      |
| Forearm Internal Rotation*              | Wrist/Forearm        | Guided practice of rotational forearm movement and distal upper-limb control.                                        |
| Forearm External Rotation*              | Wrist/Forearm        | Guided practice of rotational forearm movement and distal upper-limb control.                                        |

\* Included for movement familiarization and therapeutic practice but excluded from quantitative performance evaluation due to the limited reliability of Kinect-based wrist and forearm rotational tracking.

Although neither the **FMA-UE** nor the **WMFT** define a standardized kinematic calibration protocol, both assessments are grounded in clinically relevant upper-limb movement domains.

The calibration movement set was therefore designed as a clinically informed approximation of these underlying motor domains rather than a direct replication of individual test items. In particular, the selected movements capture key kinematic primitives commonly associated with func-

tional upper-limb use in post-stroke rehabilitation, including vertical reaching (shoulder flexion and abduction), cross-body reaching (horizontal adduction), and elbow flexion-extension required for workspace exploration.

Distal wrist and forearm movements were included for therapeutic familiarisation but were not considered primary calibration targets due to the reduced reliability of Kinect v2 skeletal tracking for fine-grained distal kinematics. In contrast, shoulder and elbow joints provide more robust and anatomically consistent estimates of functional range of motion in vision-based tracking systems.

The resulting calibration protocol therefore represents a functionally grounded upper-limb range-of-motion profile intended to support personalised task scaling within the rehabilitation environment rather than to provide a clinical-grade biomechanical measurement of joint limits.

Short recovery intervals were incorporated between calibration movements to reduce the influence of transient muscular fatigue and allow patients to return to a neutral posture before initiating the subsequent movement task.

Although wrist flexion, extension, and forearm rotational movements are included within the guided calibration sequence to encourage distal upper-limb practice and movement familiarization, quantitative assessment and exercise personalization are primarily based on shoulder and elbow movements. Previous validation studies have demonstrated that Kinect-based skeletal tracking provides greater reliability for proximal upper-limb kinematics than for distal wrist and forearm movements. Furthermore, forearm pronation and supination are not directly represented within the Kinect skeletal model and must therefore be estimated indirectly from hand orientation relative to the forearm axis. Because these measurements are substantially more sensitive to tracking uncertainty, wrist and forearm exercises were excluded from quantitative rehabilitation scoring and are used solely for guided practice.

Fine finger articulation was similarly excluded from the calibration procedure because Kinect v2 does not provide sufficiently stable or anatomically reliable finger-level motion measurements for consistent rehabilitation assessment.

To ensure that movements are performed according to their intended therapeutic objective, several calibration tasks incorporate plane-specific movement constraints derived from the movement definitions used within the **FMA-UE**. Coronal-plane constraints are applied during shoulder abduction tasks, sagittal-plane constraints during shoulder flexion tasks, and horizontal-plane constraints during cross-body reaching activities. These restrictions reduce the likelihood of compensatory movement strategies and improve consistency between automated assessment and established clinical evaluation procedures. To accommodate normal movement variability and Kinect tracking uncertainty, movement validation was performed using predefined angular tolerance margins rather than exact trajectory matching.

In addition to movement-specific validation criteria, the system provided real-time visual feedback when excessive compensatory behaviour or incorrect movement execution was detected, encouraging patients to adjust their posture and movement pattern before continuing the task. Calibration measurements were derived only from movements satisfying the predefined validity

criteria. A detailed description of the compensation monitoring framework and associated feedback mechanisms is provided in Subsection 4.6.4.

The maximum valid movement amplitudes achieved during calibration are stored within the patient profile as two scalar limits per arm. Measurements obtained during periods of excessive compensation or violations of movement-specific validation criteria are excluded from the calibration process. The resulting limits therefore represent the patient's highest successfully executed movements while maintaining the required movement pattern.

#### 4.8.1.2 Movement Monitoring and Performance Evaluation

All rehabilitation modules share a common movement monitoring and performance evaluation framework. During gameplay, Kinect-based skeletal tracking continuously records upper-limb and trunk kinematics, allowing the system to assess movement execution quality, detect compensatory strategies, and estimate clinically relevant performance measures.

Movement quality is evaluated using a combination of task-specific performance metrics and kinematic indicators. Regardless of the active rehabilitation module, the system computes movement smoothness using the **SPARC** metric described in Subsection 4.6.3. Smoothness values are subsequently incorporated into both performance assessment and adaptive difficulty regulation.

To provide clinically meaningful rehabilitation feedback, all games additionally integrate movement assessment components inspired by the **FMA-UE** and the **WMFT**. Rather than evaluating all assessment items simultaneously, the framework activates only the movement components relevant to the therapeutic objectives of the current task. This movement-specific assessment strategy allows clinical evaluation to remain aligned with the motor demands of each rehabilitation activity while reducing the influence of unrelated movement components.

Performance outcomes generated by the assessment framework are combined with gameplay-specific metrics, such as task accuracy or completion rate, to produce composite performance scores used for rehabilitation monitoring and **DDA**.

#### 4.8.1.3 Compensation Monitoring and Corrective Feedback

To encourage movement execution through active upper-limb mobilization rather than compensatory body strategies, all rehabilitation modules incorporate a common compensation monitoring framework. Using Kinect skeletal tracking, the system continuously evaluates forward trunk lean, lateral trunk lean, and shoulder elevation relative to the patient's neutral posture.

The compensation measures are combined into the Compensation Index described in Section 4.6.5. When excessive compensation is detected, multimodal corrective feedback is provided through visual messages, auditory cues, and posture-related prompts. Depending on the rehabilitation module, compensation events may temporarily interrupt task interaction or be recorded for therapist review without affecting gameplay progression. Although illustrated using the Clean the Window module, the visual feedback mechanisms shown in Figure 4.14b are representative of the feedback strategy implemented across all rehabilitation games.

This approach promotes awareness of compensatory movement patterns while maintaining rehabilitation accessibility for patients with varying levels of motor impairment.

#### 4.8.1.4 Adaptive Difficulty and Progress Tracking

Three of the four rehabilitation modules (Clean the Window, Catch the Object, and Capsule Sorting) are integrated with the **DDA** framework described in Subsection 4.7.2.1. Following completion of each rehabilitation task, patient performance is evaluated using the common assessment pipeline and used to update the current difficulty state. In contrast, the Imitation Game employs therapist-defined rehabilitation sequences and therefore does not incorporate automatic difficulty adaptation.

The adaptive framework continuously modifies game-specific parameters according to patient performance while maintaining a consistent adaptation strategy across all rehabilitation modules. Depending on the active game, adjustable parameters may include target size, time constraints, object speed, workspace coverage, trajectory complexity, or task quantity requirements.

Following each completed task, the system independently determines whether the patient progresses to the next rehabilitation level and whether the difficulty level should be modified. Table 4.7 summarizes the possible outcomes of this decision process.

Table 4.7: General decision logic of the adaptive difficulty framework.

| Task outcome                     | Level progression         | Difficulty adaptation       |
|----------------------------------|---------------------------|-----------------------------|
| Passed and $DDA_{comp} \geq T_r$ | Advance to the next level | Increase difficulty         |
| Passed and $DDA_{comp} < T_r$    | Advance to the next level | Maintain current difficulty |
| Failed                           | Repeat the current level  | Decrease difficulty         |

where  $T_r$  denotes the predefined threshold of the composite **DDA** score used to determine whether the task difficulty should be increased.

By adapting task demands according to observed motor performance, the framework aims to maintain an appropriate challenge level throughout rehabilitation, supporting engagement while minimizing frustration and excessive compensatory behaviour.

All performance metrics, assessment outcomes, compensation measurements, and difficulty states are stored within the patient rehabilitation profile. This information supports longitudinal monitoring of recovery progress and allows rehabilitation sessions to resume from the previously achieved state.

#### 4.8.2 Game 1: Clean the Window

The Clean the Window rehabilitation module was developed as a continuous upper-limb tracing exercise intended to promote repetitive reaching movements, movement trajectory control, and sustained motor engagement within a task-oriented virtual environment. The game integrates

Kinect-based skeletal tracking with real-time movement evaluation and adaptive rehabilitation regulation.

#### 4.8.2.1 Therapeutic Objective

The primary therapeutic objective of the module is to encourage repeated upper-limb movement across different regions of the patient's reachable workspace while reducing compensatory trunk involvement.

As illustrated in Figure 4.11, the tracing templates vary in spatial coverage and trajectory complexity in order to promote different movement demands throughout rehabilitation progression.

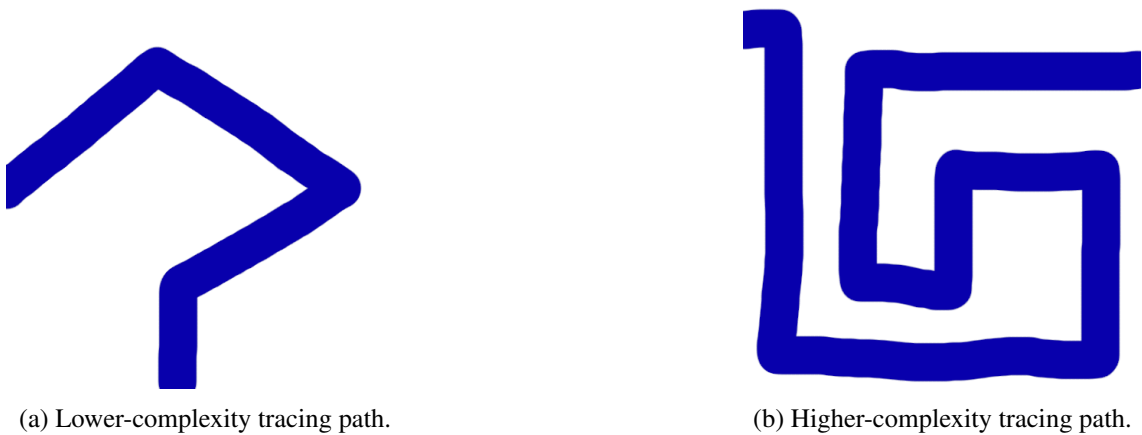


Figure 4.11: Examples of tracing patterns used in the Clean the Window rehabilitation module with different movement complexity levels.

By requiring patients to follow predefined movement paths, the exercise aims to stimulate shoulder and elbow mobilization, movement precision, and directional control while maintaining a high level of task repetition during rehabilitation practice.

The tracing templates used within this module were implemented as image-based trajectory masks defining valid interaction regions over the virtual surface. By modifying the spatial arrangement and geometric complexity of these templates, rehabilitation tasks can emphasize different movement amplitudes, directions, and coordination demands.

To support therapist-driven rehabilitation personalization, the platform additionally allows custom tracing templates to be externally created and imported into the system. This functionality enables therapists to design exercise trajectories adapted to specific rehabilitation objectives, patient limitations, or targeted movement patterns while maintaining the same gameplay interaction framework.

#### 4.8.2.2 Gameplay Interaction

During gameplay, the patient interacts with a virtual window surface using the affected hand tracked through the Kinect v2 sensor. The rehabilitation task consists of following predefined



tracing paths distributed across the window surface in order to progressively clean the virtual environment. Hand position was obtained from the Kinect v2 skeletal tracking system and projected onto the virtual window surface through a ray-casting procedure against the window collider. The resulting intersection point was converted into UV texture coordinates, which were subsequently mapped to texture pixel coordinates

$$(u \times \text{width}, v \times \text{height})$$

These coordinates defined the centre of a circular interaction brush with radius  $r_{\text{brush}}$ , where  $r_{\text{brush}}$  is an adaptive gameplay parameter regulated by the DDA framework.

Tracing trajectories were represented as image-based masks, allowing rehabilitation paths to be defined independently of the game logic. Target regions were identified using HSV colour threshold applied to a calibrated blue hue range within the source texture. This approach enabled therapists to create and import custom tracing templates while preserving a consistent interaction mechanism.

For each frame, all pixels located within the brush radius were evaluated relative to the target trajectory. Pixels corresponding to valid trajectory regions were marked as correctly traced and rendered in green. Pixels outside the target path were rendered in red to indicate inaccurate tracing behaviour. To avoid penalizing patients while initially locating the trajectory, off-path interactions were only registered after the patient had first established contact with a valid trace region during the current task. Subsequent deviations from the active trajectory were then highlighted in real-time to support movement correction and error awareness. Examples of correct and incorrect tracing behaviour are shown in Figure 4.12 and Figure 4.13, respectively.



Figure 4.12: Correct tracing of the predefined trajectory, with valid interactions highlighted in green.





Figure 4.13: Deviation from the predefined trajectory, with off-path interactions highlighted in red.

Task completion is determined exclusively by valid interaction within predefined target regions.

#### 4.8.2.3 Multimodal Feedback

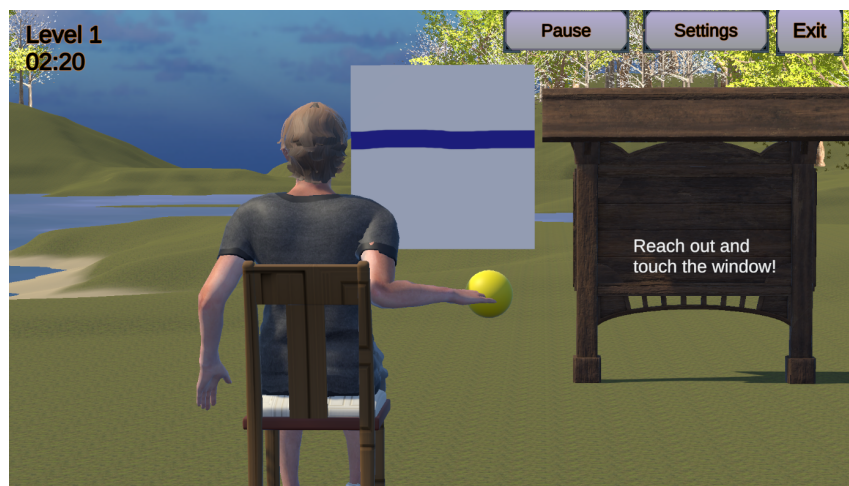
The patient's hand is represented by a virtual cursor whose colour changes according to the current interaction state, providing continuous feedback regarding task execution. When the cursor is not in contact with the tracing surface, it is displayed in yellow, indicating that no active interaction with the window is occurring, as illustrated in Figure 4.14a. Visual instructions are presented together with spoken audio prompts to guide the patient towards the target interaction area.

Contact with valid tracing regions is represented in green, allowing the patient to progressively clean the target trajectory, whereas movements performed outside the predefined tracing path are displayed in red, indicating inaccurate tracing behaviour.

To discourage compensatory movement strategies, the cursor changes to black whenever excessive trunk displacement is detected. During these periods, tracing interaction is temporarily suspended and corrective feedback is provided until the patient returns to an acceptable postural position, as shown in Figure 4.14b. Areas successfully traced by the patient are progressively cleaned, providing continuous visual feedback regarding task progress and tracing accuracy.

During compensation events:

- the interaction cursor changes to black;
- a visual warning message is displayed;
- a voice prompt instructs the patient to correct posture.



(a) Yellow cursor state indicating no contact with the tracing surface.



(b) Detection of excessive trunk displacement with visual corrective feedback.

Figure 4.14: Examples of visual feedback states in the Clean the Window rehabilitation module.

Normal gameplay interaction resumes automatically once the patient returns to an acceptable postural position. This multimodal feedback strategy was designed to reinforce movement awareness while encouraging upper-limb mobilization with reduced compensatory body leaning.

#### 4.8.2.4 Performance Evaluation

Performance evaluation follows the common assessment framework described in Section 4.8.1.2. For this module, assessment primarily focuses on tracing accuracy, movement smoothness, and the quality of reaching movements required to follow the target trajectories.

Tracing accuracy is computed from the proportion of correctly covered trajectory regions relative to movements performed outside the intended path. These metrics are subsequently incorporated into rehabilitation scoring and adaptive difficulty regulation.

The **FMA-UE** item mask restricts scoring to Item II-B (shoulder flexion), Item II-C (shoulder abduction), and Item III-B (elbow extension). The **WMFT** item mask restricts scoring to **WMFT-01** (forearm to table), **WMFT-02** (forearm to box), and **WMFT-03** (elbow extension).

This assessment selection reflects the continuous tracing movements required throughout the Clean the Window task. Following the predefined trajectories requires repeated shoulder flexion, shoulder abduction, and elbow extension over a large portion of the calibrated workspace while maintaining smooth, controlled movement execution. Consequently, the selected assessment items capture both the movement amplitudes and functional reaching abilities that are most directly exercised during gameplay.

#### 4.8.2.5 Level Structure and Progression

The rehabilitation progression combines two complementary mechanisms. First, predefined rehabilitation levels introduce progressively more demanding tracing templates by increasing trajectory complexity and workspace coverage. Second, within each level, the **DDA** framework continuously adjusts gameplay parameters, such as the time limit, brush size, and required completion percentage, according to patient performance. Consequently, patients perform the same tracing template under individualized task conditions while the overall rehabilitation progression remains defined by the level structure.

The **DDA** framework dynamically adjusts task difficulty within this module through modifications to key gameplay parameters, including tracing time limits, required completion percentages, and interaction brush size.

Table 4.8 summarizes the gameplay parameters regulated by the **DDA** framework within the Clean the Window module.

Table 4.8: Gameplay parameters adapted by the **DDA** framework

| Parameter                    | Easy  | Hard  | Purpose                                    |
|------------------------------|-------|-------|--------------------------------------------|
| Time limit                   | 160 s | 60 s  | Promotes faster task execution             |
| Brush size                   | 65 px | 55 px | Increases tracing precision requirements   |
| Required trajectory coverage | 80%   | 95%   | Requires more complete trajectory coverage |

A tracing task becomes eligible for completion when the patient cleans the required proportion of the predefined tracing path. This required trajectory coverage is determined by the current **DDA** difficulty level, varying continuously between 80% and 95%, as described in Table 4.8. If this percentage is not reached before the allocated time expires, the task is considered unsuccessful. A motivational message is displayed and the same tracing task is restarted using the updated difficulty determined by the **DDA** framework.

Once the required trajectory coverage has been achieved, the task is evaluated against the remaining passing criteria described in Equation 4.26. If all criteria are satisfied, the rehabilitation

session proceeds seamlessly to the next level, presenting a new tracing template while preserving the updated **DDA** difficulty. If any of the passing criteria are not met, a motivational message is displayed and the current level is repeated using the newly adjusted difficulty level.

#### **4.8.2.6 Clinical Relevance**

The Clean the Window module was designed to promote continuous upper-limb movement execution across large regions of the reachable workspace. Unlike discrete reaching tasks, the tracing activity requires sustained regulation of movement direction, arm position, and trajectory accuracy throughout extended movement sequences.

By combining continuous reaching with visuomotor guidance, the task encourages movement precision, workspace exploration, and prolonged motor engagement. The progressive increase in trajectory complexity further allows rehabilitation intensity to evolve alongside patient recovery while preserving a familiar interaction paradigm.

### **4.8.3 Game 2: Catch the Object**

The Catch the Object module is a rehabilitation game designed to promote upper-limb use through object interception tasks performed within a virtual environment. Patients control a virtual bucket using movements of the affected arm and attempt to intercept falling objects distributed across the game area. The module combines motor training with visuomotor coordination, reaction demands, and adaptive difficulty progression.

#### **4.8.3.1 Therapeutic Objective**

The primary therapeutic objective of the Catch the Object module is to promote active use of the affected upper limb through repeated goal-directed reaching movements. Patients must continuously reposition the arm to intercept visually presented targets, encouraging shoulder abduction, elbow extension, movement initiation, and exploration of the available reaching workspace.

The exercise follows task-oriented rehabilitation principles by requiring purposeful interaction with dynamic visual stimuli rather than isolated joint movements. As rehabilitation progresses, increasing task demands encourage improved movement coordination, reaction speed, and visuomotor integration.

#### **4.8.3.2 Gameplay Interaction**

During gameplay, the patient controls a virtual bucket using the affected hand tracked by the Kinect v2 sensor. The objective is to position the bucket beneath falling objects and intercept them before they reach the bottom of the game environment and under time pressure.

Each task begins only after the patient initiates a deliberate movement of the affected wrist. Movement initiation is detected when wrist displacement from a resting baseline exceeds a pre-defined threshold of 8 cm obtained empirically. Object spawning, and therefore task timing, is

contingent on active patient-initiated movement rather than a fixed countdown delay. This design encourages voluntary movement initiation and ensures that rehabilitation activity begins only when the patient is prepared to engage with the task, while allowing for a brief rest.

Successful interception requires the falling object to enter the bucket from above. Contacts occurring from the side or from below are not registered as valid catches. This constraint ensures that patients must actively position the bucket beneath the falling object, reinforcing the intended reaching and object-tracking behaviour rather than allowing incidental collisions.

Object spawning locations are constrained to the patient-specific reachable workspace established during calibration, ensuring that targets remain physically accessible while encouraging active exploration of the available movement range.

Depending on the rehabilitation level, gameplay may require interception of all falling objects or selective interception of specific target objects while avoiding distractors. This progression introduces increasing cognitive demands while preserving the same underlying interaction mechanics.

Figure 4.15 illustrates the gameplay progression within the Catch the Object module. Initially, patients are required to intercept all falling objects. At more advanced rehabilitation levels, the task introduces selective interception, requiring patients to catch only the designated target objects while avoiding distractors, thereby increasing the cognitive demands of the exercise.





(a) Introductory level, where all falling objects are considered valid targets.



(b) Advanced level requiring selective interception of target objects while avoiding distractors.

Figure 4.15: Gameplay progression in the Catch the Object rehabilitation module.

#### 4.8.3.3 Multimodal Feedback

The module provides continuous visual and auditory feedback to guide the patient throughout task execution. At the beginning of each rehabilitation task, the game presents the exercise instructions both visually and through an auditory cue, ensuring that the patient understands the objective before object spawning begins. Since gameplay is initiated only after a deliberate movement of the affected wrist, an additional visual message and auditory prompt encourage the patient to perform the initial movement required to start the task.

During gameplay, a real-time counter displays the number of successfully intercepted objects, while a countdown timer indicates the remaining task duration, with increased visual emphasis during the final seconds of the task. Each successful interception is immediately acknowledged

by removing the intercepted object from the game environment, updating the catch counter, and playing a short confirmation sound, providing immediate positive reinforcement.

Corrective feedback associated with compensation monitoring follows the common framework described in Section 4.6.4. Object interceptions performed while trunk compensation is detected are excluded from both the successful catch count and the accuracy calculation. During compensation events, the patient receives synchronized visual and audio corrective feedback prompting posture correction. Feedback is presented in the language selected for the rehabilitation session, supporting both English and Portuguese-speaking users.

#### 4.8.3.4 Performance Evaluation

Performance evaluation follows the common assessment framework described in Section 4.8.1.2, instantiated using module-specific assessment masks. For this module, assessment primarily focuses on interception accuracy, movement smoothness, and the quality of the reaching movements required to intercept falling objects.

Interception accuracy is computed from the proportion of successfully intercepted target objects relative to the total number of relevant interception opportunities.

The **FMA-UE** item mask restricts scoring to Item II-C (shoulder abduction range), Item III-B (elbow extension during lateral reaching), Item V-A (combined shoulder abduction with elbow extension). The **WMFT** item mask restricts scoring to **WMFT-01** (shoulder abduction sweep) and **WMFT-03** (elbow extension angle).

This assessment selection reflects the predominantly lateral reaching movements required to intercept falling objects using the virtual bucket, emphasizing shoulder abduction and elbow extension rather than the forward-reaching or lifting movements emphasized in other rehabilitation modules.

#### 4.8.3.5 Level Structure and Progression

The Catch the Object module is organized into multiple rehabilitation levels, each introducing progressively greater motor and cognitive demands through predefined gameplay configurations. Progression between levels is achieved by modifying characteristics such as object-selection complexity, the number of required catches, spawning frequency, and baseline object speed.

Within each rehabilitation level, the number of required catches is fixed but task difficulty is further personalized by the **DDA** framework. The **DDA** continuously adjusts selected gameplay parameters within predefined limits associated with the current level. Consequently, each level defines a range of parameter values spanning from an easier to a more challenging configuration, allowing the task to be individualized while preserving the intended rehabilitation objectives of that level.

Table 4.9 summarizes the gameplay parameters adapted by the **DDA** framework within each rehabilitation level.

Table 4.9: Gameplay parameters adjusted by the DDA framework within each rehabilitation level of the Catch the Object module.

| Parameter        | Easy        | Hard              | Purpose                                          |
|------------------|-------------|-------------------|--------------------------------------------------|
| Object speed     | Slow        | Fast              | Promotes faster movement initiation and reaction |
| Spawn interval   | Long        | Short             | Increases task intensity and movement frequency  |
| Required catches | Low         | High              | Requires greater task completion performance     |
| Target selection | All objects | Selective targets | Introduces cognitive discrimination demands      |

#### 4.8.3.6 Clinical Relevance

The Catch the Object module promotes repeated goal-directed reaching movements while simultaneously engaging visuomotor coordination, reaction speed, and selective attention processes. Unlike continuous trajectory-following exercises, the task requires rapid movement initiation and frequent repositioning of the upper limb in response to changing visual stimuli.

The calibration-based adaptation of object spawning locations ensures that training remains individualized to each patient's functional reaching capacity while encouraging progressive exploration of the available workspace.

The integration of object discrimination tasks at higher difficulty levels further combines motor execution with cognitive processing demands, including stimulus selection, decision-making, and movement planning. Together with adaptive difficulty regulation and compensation monitoring, these characteristics support individualized rehabilitation while promoting functional upper-limb use.

#### 4.8.4 Game 3: Capsule Sorting Game

The Capsule Sorting Game is a Kinect-based rehabilitation module in which patients intercept virtual capsules and transport them to colour-matched target zones displayed within a virtual environment. The task combines reaching, object transport, visuomotor coordination, and colour discrimination within a goal-directed rehabilitation activity. Through adaptive adjustment of task complexity and continuous monitoring of movement quality, the module provides individualized upper-limb training while simultaneously collecting performance and assessment metrics for rehabilitation monitoring.



#### 4.8.4.1 Therapeutic Objective

The primary therapeutic objective of the Capsule Sorting Game is to encourage patients to perform repeated reaching and arm transport movements across different regions of their available workspace, promoting upper-limb motor activation with appropriate range of motion, movement quality, and spatial accuracy.

The exercise is based on object manipulation and sorting. Capsules are spawned at random locations within the patient-specific reachable workspace established during calibration. Patients are required to reach for each capsule, and transport it to the target zone corresponding to its colour. This interaction encourages repeated reaching, object transport, and controlled arm movements throughout the workspace, promoting shoulder abduction, shoulder flexion, and elbow extension, movement components frequently impaired following stroke and commonly addressed during upper-limb rehabilitation.

#### 4.8.4.2 Gameplay Interaction

During gameplay, coloured capsules are spawned at random locations within the patient-specific reachable workspace established during calibration. Patients interact with the virtual environment using the affected hand tracked by the Kinect v2 sensor. The rehabilitation task consists of reaching for each capsule and transporting it to the target zone with the corresponding colour. Restricting capsule generation to the calibrated interaction space ensures that all objects remain reachable while encouraging repeated exploration of different regions of the patient's functional workspace.

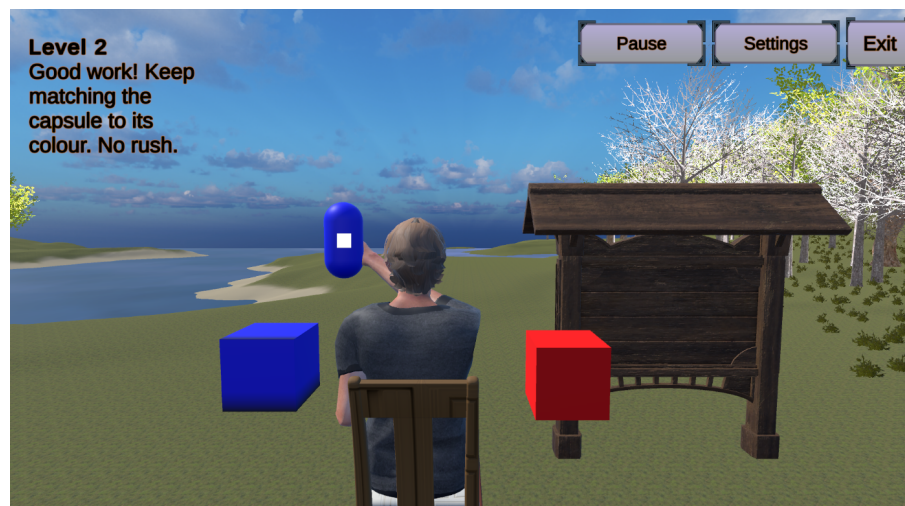
The coloured target zones are positioned using the patient-specific reachability limits obtained during the calibration procedure. Specifically, the left and right target zones are placed near the maximum lateral reach of the affected arm. Consequently, the task promotes repeated reaching across a large range of motion while remaining achievable for patients with varying levels of motor impairment.

At the beginning of each rehabilitation task, the game waits for the patient to initiate movement before capsule spawning begins, ensuring that task execution is initiated voluntarily rather than by a fixed countdown.

Figure 4.16 illustrates two examples of the Capsule Sorting module. The initial rehabilitation levels use a single target colour and a reduced number of capsules, minimising both motor and cognitive demands. As rehabilitation progresses, additional target colours and capsules are introduced, requiring patients to simultaneously perform reaching, object manipulation, colour discrimination, and decision-making.



(a) Early rehabilitation level with a single target colour.



(b) More advanced rehabilitation level with multiple target colours.

Figure 4.16: Examples of gameplay in the Capsule Sorting rehabilitation module at different rehabilitation levels.

Following completion of each task, patient performance is evaluated using the common assessment and **DDA** framework. Successful completion advances the patient to the next rehabilitation level, whereas unsuccessful attempts result in repetition of the current level with the difficulty adapted to the patient's demonstrated performance. Brief rest periods are provided between levels to minimise fatigue and maintain engagement throughout the rehabilitation session.

#### 4.8.4.3 Multimodal Feedback

The module provides continuous visual feedback regarding task progress and sorting performance. Before gameplay begins, both visual and auditory instructions prompt the patient to initiate the

rehabilitation task by moving the affected upper limb. Capsule spawning only starts after this movement is detected, ensuring that each rehabilitation task is initiated voluntarily.

During gameplay, colour-coded target zones assist capsule classification, while successful placements are immediately confirmed through visual reinforcement. Incorrect capsule placements are immediately indicated by a brief yellow flashing animation, after which the capsule automatically returns to its original position, allowing the patient to attempt the sorting task again. Capsules that are not sorted before their lifetime expires are removed from the game environment and counted as unsuccessful attempts. These feedback mechanisms provide continuous **KR** throughout task execution.

To improve object visibility during reaching movements, each capsule is accompanied by a white visual indicator that remains visible even when the capsule becomes partially occluded by the patient's body from the Kinect's viewpoint. This design assists patients in locating target objects throughout the interaction and reduces the impact of temporary visual occlusions during gameplay.

Level instructions and task information indicators are displayed through a heads-up display interface. All interface elements, instructional messages, and audio prompts are available in both English and Portuguese.

Compensation monitoring follows the common framework. When excessive trunk compensation is detected during capsule transport, synchronized visual and audio feedback prompts the patient to correct posture and reduce compensatory movement strategies.

#### 4.8.4.4 Performance Evaluation

Performance evaluation follows the common assessment, instantiated using module-specific assessment masks. For this module, assessment primarily focuses on capsule-sorting accuracy, movement smoothness, and the quality of reaching and transport movements required to intercept and place capsules within the appropriate target zones.

Sorting accuracy is computed from the proportion of correctly placed capsules relative to the total number of sorting opportunities.

The **FMA-UE** item mask restricts scoring to Item III-B (elbow extension), Item IV-B (shoulder flexion) and Item V-A (shoulder abduction). The **WMFT** item mask restricts scoring to **WMFT-01** (shoulder abduction sweep), **WMFT-03** (elbow extension), and **WMFT-08** (reach-and-retrieve movement).

This assessment selection reflects the combination of reaching, transport, and object-placement movements required throughout the capsule-sorting task.

#### 4.8.4.5 Level Structure and Progression

The Capsule Sorting Game is organized into multiple rehabilitation levels, each defined by a specific configuration of motor and cognitive task demands. Progression is achieved through modifications to capsule lifetime, the number of simultaneously active capsules, and the number of

distinct capsule colours that must be sorted.

Adaptive difficulty adjustment is applied through the common **DDA** framework. Within this module, adjustable parameters include capsule lifetime, maximum active capsule count, and colour discrimination complexity.

Each rehabilitation level defines a fixed number of capsules that must be correctly sorted to complete the task. While this completion requirement remains constant within a given level, the **DDA** framework adapts the gameplay conditions under which the task is performed by modifying the parameters listed in Table 4.10.

Table 4.10: Adaptive parameters modified by the **DDA** framework in the Capsule Sorting Game.

| Parameter        | Easy | Hard  | Purpose                                                          |
|------------------|------|-------|------------------------------------------------------------------|
| Capsule lifetime | Long | Short | Increases time pressure and movement speed requirements          |
| Active capsules  | One  | Many  | Increases simultaneous motor and cognitive demands               |
| Target colours   | One  | Many  | Increases colour discrimination and decision-making requirements |

#### 4.8.4.6 Clinical Relevance

The Capsule Sorting Game targets reaching, transport, and object-placement movements commonly addressed during upper-limb stroke rehabilitation. Unlike interception-only tasks, the module requires patients to coordinate multiple movement phases, including target acquisition, object transport, and accurate placement within a designated location.

The task additionally incorporates cognitive demands through colour discrimination and target selection, requiring patients to identify the appropriate destination before executing the transport movement. As difficulty increases, these perceptual and decision-making demands become progressively more challenging while preserving the same underlying motor interaction.

By combining individualized workspace calibration, adaptive difficulty regulation, and multi-modal performance assessment, the module supports personalized rehabilitation while promoting functional upper-limb use in a goal-directed environment.

#### 4.8.5 Game 4: Imitation Game

The Imitation Game rehabilitation module was developed as a therapist-configurable exercise execution environment designed to promote accurate reproduction of upper-limb rehabilitation movements through observational learning and guided motor practice. Unlike task-oriented rehabilitation games that embed movements within virtual activities, this module focuses directly on the execution of predefined therapeutic movement sequences demonstrated by a virtual instructor avatar.

The game integrates Kinect-based skeletal tracking, real-time posture monitoring, and movement assessment mechanisms to support structured rehabilitation exercises prescribed by therapists through the external Rehab Sequence Editor application.

#### **4.8.5.1 Therapeutic Objective**

The primary therapeutic objective of the Imitation Game is to promote accurate execution of upper-limb rehabilitation movements through observational learning and guided motor practice. Patients are required to reproduce movements demonstrated by a virtual instructor avatar, encouraging active engagement of motor planning, movement execution, and sensorimotor integration processes.

Unlike the task-oriented rehabilitation games included in the platform, this module focuses directly on the practice of prescribed therapeutic movements rather than embedding them within a gameplay objective. This allows rehabilitation exercises to target specific movement components, including shoulder, elbow, wrist, and forearm actions, according to the patient's therapeutic needs.

#### **4.8.5.2 Gameplay Interaction**

During gameplay, the patient observes a virtual instructor avatar performing a rehabilitation movement and subsequently attempts to reproduce the demonstrated posture using the affected upper limb.

Each exercise follows a two-stage interaction process. During the demonstration phase, the instructor avatar presents the target movement, allowing the patient to observe the intended posture and movement trajectory. Once the demonstration is completed, the system enters an imitation phase during which the patient attempts to reproduce the movement within the prescribed execution interval. Figure 4.17 illustrates the complete interaction workflow, including the demonstration phase, real-time imitation, and the performance summary presented at the end of the exercise.





(a) Exercise initialization. The virtual instructor demonstrates the rehabilitation movement while the patient observes the target posture before beginning the imitation phase.



(b) Real-time imitation phase. The patient's movements are captured by the Kinect sensor and represented by the patient avatar while the movement is continuously compared with the demonstrated posture.



(c) Exercise performance achieving 100% accuracy.

Figure 4.17: Workflow of the Imitation Game, illustrating the demonstration, imitation, and performance feedback stages of a rehabilitation exercise.

Throughout the imitation phase, Kinect-based skeletal tracking continuously captures upper-limb motion and updates a patient avatar in real-time. The recorded movement is compared with the demonstrated posture to evaluate imitation performance and provide corrective feedback.

The rehabilitation session progresses sequentially through the prescribed exercise protocol, alternating between demonstration and imitation phases until all exercises have been completed.

#### 4.8.5.3 Multimodal Feedback

The system provides contextual corrective feedback based on real-time movement analysis. Feedback messages are displayed dynamically according to the specific movement being performed and the detected execution errors. Examples include instructions encouraging additional arm elevation, greater cross-body reaching, increased elbow flexion, or improved alignment with the demonstrated posture.

Movement-specific feedback is generated through a movement definition dictionary that associates each rehabilitation movement with its expected anatomical movement plane and corresponding evaluation assessment mask. This abstraction allows the feedback system to remain independent of predefined exercises, enabling therapist-created customized movements to automatically inherit appropriate movement-plane validation and corrective feedback mechanisms.

Several movement-quality monitoring mechanisms contribute to the feedback system. For shoulder movements, the system evaluates whether arm motion is occurring within the intended movement plane. If the patient performs a movement in an incorrect plane, corrective messages are displayed encouraging redirection of the arm toward the appropriate trajectory. Figure 4.18 illustrates an example in which the target movement is a lateral arm elevation, but the patient raises the arm in front of the body. The system detects the incorrect movement plane and provides corrective feedback instructing the patient to move the arm laterally.



Figure 4.18: Example of real-time movement-specific corrective feedback displayed during the imitation phase.

Movement velocity is continuously monitored throughout exercise execution. In the current implementation, a threshold of  $60^\circ/\text{s}$  was empirically selected during system development to identify movements performed with excessive speed. When this threshold is exceeded, corrective feedback encourages slower and more controlled execution.

The trunk compensation monitoring framework described in Subsection 4.6.4 is also integrated into the Imitation Game. When compensatory trunk movements are detected, corrective visual and auditory feedback is provided; however, the exercise is not interrupted and task progression is not blocked. This design choice reflects the role of the module as a therapist-guided rehabilitation environment rather than a fully autonomous assessment system.

When no significant movement errors are detected, positive reinforcement messages are displayed to indicate satisfactory alignment with the demonstrated movement and encourage continuation of the exercise.

#### 4.8.5.4 Performance Evaluation

For this module, assessment primarily focuses on posture imitation accuracy, movement smoothness and the quality of the reproduced therapeutic movement.

Movement assessment is based on comparison between the posture demonstrated by the instructor avatar and the best posture achieved by the patient during the imitation interval. Upper-limb posture is represented using arm elevation angle, elbow angle, and upper-arm direction vectors extracted from Kinect skeletal tracking data.

For shoulder-dominant exercises, imitation accuracy is computed as a weighted combination of elevation similarity and directional similarity. Additional penalties are applied when movement execution deviates substantially from the intended movement plane, preventing high imitation scores from being achieved through biomechanically different movement strategies.

The assessment framework evaluates not only movement amplitude but also movement direction, ensuring that patients reproduce the intended therapeutic movement rather than achieving the target posture through alternative movement strategies.

Movement smoothness is quantified using the **SPARC** metric computed from the recorded hand trajectory, while peak movement velocity is monitored to identify excessively rapid executions that may reflect reduced motor control or momentum-assisted movement strategies.

The **FMA-UE** and **WMFT** assessment masks are selected dynamically according to the exercise prescribed within the rehabilitation sequence. This approach allows clinically relevant movement components to be evaluated while preserving consistency with the common assessment framework used throughout the rehabilitation platform.

#### 4.8.5.5 Rehabilitation Protocol Configuration

Before rehabilitation gameplay begins, the therapist is presented with a session configuration panel that allows selection of the exercise sequence to be performed during the rehabilitation session. This interface provides three alternative workflow options:



- loading the most recently executed rehabilitation sequence;
- importing an existing rehabilitation sequence from a JSON file;
- creating a new rehabilitation sequence.

When the therapist selects the sequence creation option, the external Rehab Sequence Editor application is launched. This companion application was developed specifically to support the design, modification, and management of rehabilitation exercise protocols. Figure 4.19 presents the main interface of the Rehab Sequence Editor.

## Rehab Sequence Editor

The screenshot displays the 'Rehab Sequence Editor' interface. At the top right, there is a language selector set to 'Português'. Below this, the 'Exercise Plan' section contains a text input field with the example text 'e.g., Patient John - Shoulder Rehab'. The main section is titled 'Add New Movement' and includes several configuration options: 'Arm' (set to 'Right'), 'Body Part' (set to 'Upper Arm'), 'Movement Preset' (a dropdown menu showing 'Arm Up'), 'Custom Rotation (Euler X, Y, Z)' (three input fields with values -80,0, 0,0, and 0,0), 'Duration (seconds)' (set to 4,0), and 'Pause After (seconds)' (set to 3,0). A button labeled 'Add Movement to Sequence' is positioned below these fields. At the bottom, the 'Current Sequence' section lists three items: 'Right ForeArm: Forearm Bend (Arm Flexion) (4s, pause: 3s)', 'Right ForeArm: Forearm Straight (Arm Extension) (4s, pause: 3s)', and 'Right UpperArm: Arm Mid Up (4s, pause: 3s)', with the last item highlighted.

Figure 4.19: Main interface of the Rehab Sequence Editor used to create, modify, and manage rehabilitation exercise protocols.

Within the editor, therapists can construct customized rehabilitation plans by defining an ordered sequence of upper-limb movements and configuring their associated execution parameters, including movement duration, pause intervals, target body segments, and arm laterality. The editor provides a set of predefined rehabilitation movements covering shoulder, elbow, wrist, and forearm actions, while also supporting movement customization through configurable joint rotations within predefined anatomical limits. This functionality enables exercises to be adapted to individual patient capabilities and therapeutic objectives.

To facilitate protocol design, the editor includes an interactive 3D movement visualization that displays the resulting limb posture associated with the selected rotation parameters, which can

be seen in Figure 4.20. This visual representation allows therapists to immediately inspect the configured movement and adjust joint angles more intuitively, reducing ambiguity when defining customized exercises.



Figure 4.20: Interactive 3D movement visualization in the Rehab Sequence Editor, providing a real-time preview of the limb posture corresponding to the configured joint rotations.

The editor also supports modification of previously created rehabilitation plans by loading an existing sequence file, editing its contents, and saving the updated protocol for future use. All rehabilitation plans are stored using a structured JSON format, allowing exercise protocols to be reused, modified, and shared independently of the game environment.

Once a sequence has been created or selected, the resulting exercise plan is loaded into the Imitation Game and serves as the basis for the rehabilitation session. The selected sequence determines the movements demonstrated by the instructor avatar, the order in which they are performed, and the timing characteristics associated with each exercise. This approach enables rehabilitation sessions to be individualized according to patient-specific therapeutic goals while maintaining a consistent gameplay framework.

#### 4.8.5.6 Clinical Relevance

The Imitation Game supports upper-limb rehabilitation through observational learning and guided movement reproduction, encouraging patients to practice clinically relevant movement patterns under visual supervision. Unlike the task-oriented rehabilitation games included in the platform, the module enables direct training of specific movement components prescribed by the therapist.

The ability to define individualized exercise protocols allows rehabilitation content to be adapted to different impairment levels, therapeutic goals, and stages of recovery. Combined with objective movement analysis and compensation monitoring, this flexibility supports personalized rehabilitation while promoting consistent execution of prescribed therapeutic movements.

### 4.9 Safety Considerations and System Constraints

The rehabilitation platform was designed as a low-risk, non-invasive rehabilitation support system intended to facilitate upper-limb training through motion-based interaction. Several mechanisms were incorporated to reduce the likelihood of inappropriate exercise execution and excessive physical demand during rehabilitation sessions.

Patient-specific calibration procedures establish individualized interaction boundaries based on the user's available ROM, reducing the risk of requiring movements beyond functional capabilities. During gameplay, trunk compensation monitoring provides corrective feedback when excessive postural displacement is detected, encouraging movement execution through the upper limb rather than compensatory body movements. In addition, rehabilitation sessions may be paused or terminated at any time, allowing users to manage discomfort or fatigue when necessary. To further reduce the risk of physical exhaustion and loss of motivation, the system monitors task outcomes during gameplay. When a patient fails more than three consecutive attempts within any rehabilitation module, a notification is displayed recommending a short rest period before continuing. This mechanism is intended to minimise fatigue, prevent frustration associated with repeated unsuccessful attempts, and promote sustained engagement throughout the rehabilitation session.

The adaptive difficulty framework further contributes to safe interaction by automatically reducing task complexity when sustained decreases in movement quality, task performance, or increased compensatory behaviour are observed. This mechanism aims to maintain achievable rehabilitation conditions while minimizing excessive physical or cognitive demands.

The proposed platform is intended as a rehabilitation support tool and research prototype rather than a certified medical device. It is designed to facilitate independent rehabilitation practice and therapist-guided exercise personalization but is not intended to replace professional clinical evaluation or therapeutic decision-making.

## Chapter 5

# Preliminary Feasibility and Usability Evaluation

A preliminary feasibility study was conducted to assess the usability, functionality, and overall user experience of the proposed rehabilitation platform. The objective of this evaluation was to verify the correct operation of the Kinect-based interaction mechanisms, assess the clarity of game instructions and feedback, identify potential technical limitations, and gather user perceptions regarding the rehabilitation games. The study was not intended to evaluate rehabilitation effectiveness or validate the clinical assessment framework.

### 5.1 Participants

A total of nine healthy volunteers participated in the evaluation. Participant ages ranged from 19 to 87 years (mean  $\pm$  SD:  $40.6 \pm 25.6$  years), providing feedback from both younger and older adults. The demographic characteristics of the participants are summarized in Table 5.1. The participant group included individuals with varying levels of experience with video games and motion-capture technologies, allowing evaluation across users with different levels of familiarity with interactive systems.

Table 5.1: Participant characteristics ( $n = 9$ ).

| Characteristic                           | Value                            |
|------------------------------------------|----------------------------------|
| Number of participants                   | 9                                |
| Age (years), mean $\pm$ SD               | $40.6 \pm 25.6$                  |
| Sex                                      | 5 male (55.6%), 4 female (44.4%) |
| Previous video game experience           | 6 yes (66.7%), 3 no (33.3%)      |
| Previous Kinect/motion sensor experience | 3 yes (33.3%), 6 no (66.7%)      |

Healthy volunteers were intentionally selected for this preliminary testing phase in order to identify usability issues and technical limitations before conducting evaluations involving individuals with neurological impairments. Consequently, the results obtained should be interpreted solely as indicators of system feasibility and user acceptance rather than evidence of clinical effectiveness.

Although the sample size was limited, the study was designed as a preliminary feasibility evaluation aimed at identifying usability issues and technical limitations before conducting studies involving stroke survivors.

## 5.2 Evaluation Procedure

Each participant completed an individual testing session using the rehabilitation platform.

At the beginning of the session, participants interacted with all four rehabilitation modules:

- Clean the Window;
- Catch the Object;
- Capsule Sorting Game;
- Imitation Game.

Participants were instructed to complete each game while interacting naturally with the system and following the on-screen instructions. During testing, observations were recorded regarding gameplay behaviour, movement recognition, posture monitoring, and any technical difficulties encountered.

All participants successfully completed the four rehabilitation games without requiring assistance beyond the initial explanation of the system. No testing session had to be interrupted or repeated due to software failures, although occasional tracking inaccuracies and posture-monitoring warnings were observed and recorded for later analysis.

Upon completion of the session, participants completed a post-test questionnaire designed to evaluate different aspects of the platform experience.

## 5.3 Questionnaire Design

A structured questionnaire was administered following completion of the testing session. The questionnaire consisted of Likert-scale items together with a set of open-ended questions intended to collect qualitative feedback.

The Likert-scale section employed a five-point rating scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) and evaluated the following aspects of the platform:

- Ease of use;

- Accuracy of movement recognition;
- Clarity of instructions;
- Ease of understanding the exercises;
- Appropriateness of exercise difficulty;
- Helpfulness of corrective feedback;
- Visual appeal of the virtual environment;
- Motivation provided by the games;
- Interest generated by the variety of rehabilitation activities;
- Perceived usefulness for upper-limb rehabilitation;
- Overall user satisfaction.

Participants were additionally asked to rate each rehabilitation game individually according to their overall level of satisfaction.

To obtain more detailed feedback, the questionnaire also included open-ended questions regarding the participants' favourite and least favourite games, difficulties encountered during platform use, and suggestions for future improvements.

The complete questionnaire is provided in Appendix [A](#).

## **5.4 Quantitative Results**

The corresponding mean satisfaction scores and standard deviations are presented in Figure [5.1](#). Overall, the qualitative responses indicated that participants had a positive experience when interacting with the rehabilitation platform, with most questionnaire items receiving average scores above 4 on the five-point Likert scale.

Table 5.2: Questionnaire scores obtained during the feasibility evaluation ( $n = 9$ ).

| Questionnaire Item                  | Mean | SD   |
|-------------------------------------|------|------|
| Ease of use                         | 4.11 | 0.33 |
| Instruction clarity                 | 4.67 | 0.50 |
| Exercise comprehension              | 4.67 | 0.50 |
| Difficulty appropriateness          | 4.11 | 0.78 |
| Feedback helpfulness                | 3.78 | 0.44 |
| Visual appeal                       | 4.67 | 0.50 |
| Motivation                          | 4.67 | 0.50 |
| Game variety                        | 4.89 | 0.33 |
| Perceived rehabilitation usefulness | 4.67 | 0.50 |
| Overall experience                  | 4.22 | 0.44 |

The highest mean score was obtained for game variety (4.89/5). Instruction clarity, exercise comprehension, visual appeal, motivation, and perceived rehabilitation usefulness all received mean scores of 4.67/5, indicating that participants found the platform easy to understand, engaging, and potentially useful for upper-limb rehabilitation.

Ease of use (4.11/5), overall experience (4.22/5), visual appeal (4.67/5), and the perceived appropriateness of the exercise difficulty (4.11/5) also received favourable evaluations, indicating a generally positive user experience.

The lowest-rated aspect of the platform was feedback helpfulness (3.78/5). Although this score remained above the midpoint of the scale, it indicates that participants perceived room for improvement in the corrective feedback provided during gameplay. The qualitative responses collected during the evaluation provide additional insight into the factors contributing to these ratings.

To evaluate the individual rehabilitation modules, participants also rated their overall satisfaction with each game. The corresponding mean scores and standard deviations are presented in Figure 5.1.



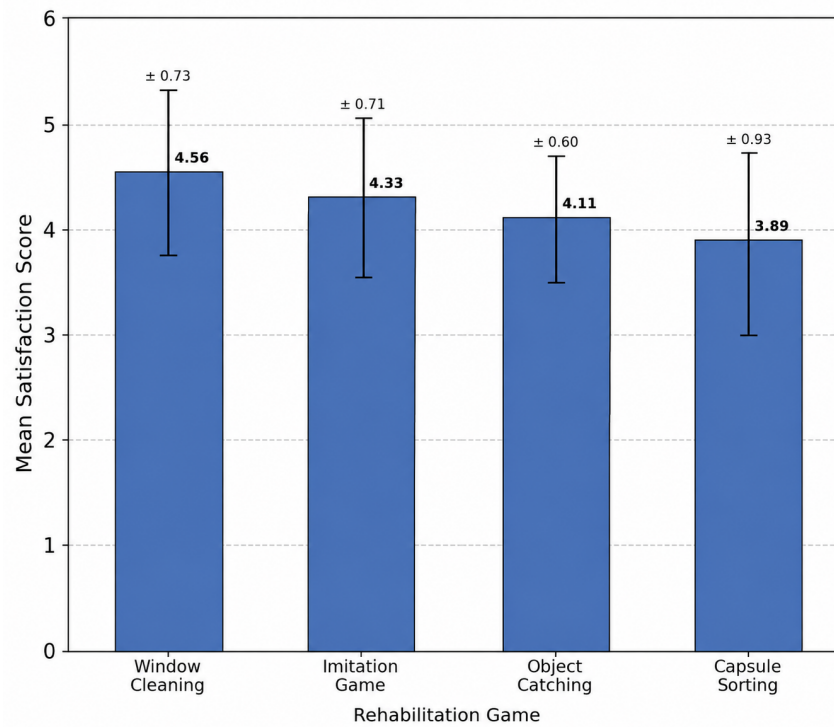


Figure 5.1: Mean participant satisfaction scores for the four rehabilitation games. Error bars represent one standard deviation ( $n = 9$ ).

The Window Cleaning Game achieved the highest satisfaction score (4.56), followed by the Imitation Game (4.33). The Object Catching Game also received favourable evaluations (4.11). The Capsule Sorting Game obtained the lowest average satisfaction score (3.89) and exhibited the highest standard deviation (0.93), indicating greater variability in participant opinions regarding this module.

## 5.5 Qualitative Feedback

The open-ended responses complemented the quantitative findings by identifying several recurring strengths and areas for improvement.

Participants consistently reported that the rehabilitation games were easy to understand, engaging, and enjoyable to complete. The Window Cleaning and Imitation games were most frequently identified as the preferred activities, primarily because they required controlled upper-limb movements and provided a more interactive experience.

Several participants also highlighted technical limitations of the current implementation. The most frequently reported issue concerned posture monitoring, with participants noting that the system occasionally detected incorrect trunk posture despite maintaining an appropriate position. Others suggested increasing the tolerance of the movement recognition algorithm and introducing a personalized calibration procedure to better accommodate differences in body dimensions and range of motion.

The Capsule Sorting Game was the activity most frequently identified as the least enjoyable. Several participants noted that some capsules spawned outside their comfortable reaching range, making the task difficult or, in some cases, impossible to complete. This observation is consistent with the lower satisfaction score obtained by this rehabilitation module.

Overall, the quantitative scores and qualitative feedback indicate that the proposed platform is usable and well accepted by healthy participants, while also identifying specific aspects of the system that should be refined before clinical evaluation.

## Chapter 6

# Discussion

### 6.1 Achievement of the Research Objectives

The primary objective of this thesis was to develop and evaluate a Kinect-based rehabilitation platform capable of supporting upper-limb rehabilitation through interactive serious games while incorporating movement assessment, adaptive difficulty regulation, compensatory movement monitoring, and therapist-guided exercise configuration. The results demonstrate that these objectives were successfully achieved.

From a technical perspective, all major system components were implemented and operated successfully within a single rehabilitation environment. The platform was capable of acquiring motion data in real-time, extracting kinematic metrics, generating assessment scores, detecting compensatory movements, adapting exercise difficulty, and providing feedback during gameplay. The successful integration of these components demonstrates the feasibility of using a single motion-capture system to support multiple rehabilitation functions simultaneously.

The preliminary evaluation further confirmed that users were able to interact with the platform successfully and complete the rehabilitation activities. High ratings for usability, exercise comprehension, and perceived rehabilitation value suggest that the system was generally intuitive and that the rehabilitation tasks were easy to understand. These are particularly important because complex rehabilitation technologies often face adoption barriers when users struggle to understand system operation or exercise objectives. This finding is particularly encouraging given that stroke rehabilitation frequently involves older adults, who may have limited prior experience with digital technologies.

At the same time, the evaluation identified several limitations that were not fully apparent during development. Issues related to workspace generation in the Capsule Sorting Game and occasional false-positive posture warnings revealed that certain components require additional personalization and refinement. Although these limitations do not affect the overall feasibility of the platform, their identification represents an important outcome of the study and provides clear directions for future development.

Overall, the work presented in this thesis demonstrates the successful implementation of a functional rehabilitation platform that combines rehabilitation exercises, movement assessment, therapist supervision, and adaptive training within a unified system. While clinical effectiveness remains to be established through future studies involving stroke survivors, the results indicate that the research objectives were achieved and that the platform provides a suitable foundation for further clinical investigation.

## 6.2 Discussion of the Rehabilitation Platform

One of the principal design goals of the proposed platform was to move beyond rehabilitation systems centred on a single repetitive exercise. The evaluation results suggest that this objective was achieved, as participants reported very high ratings for both game variety (4.89/5) and motivation (4.67/5). While the present study cannot determine whether this will translate into improved long-term adherence, the findings indicate that participants appreciated the availability of different rehabilitation activities and did not perceive the exercises as excessively repetitive.

Interestingly, participant feedback suggested that different games offered distinct rehabilitation experiences rather than simply presenting the same exercise in different visual formats. The Clean the Window game emphasized continuous arm control and movement precision, whereas the Object Catching and Capsule Sorting games required reaching, target acquisition, and object manipulation. The Imitation Game differed further by allowing therapist-directed execution of predefined movement sequences. This diversity may be particularly valuable in stroke rehabilitation, where patients often present different impairments and rehabilitation goals that cannot be adequately addressed through a single exercise type.

The integration of assessment, compensation monitoring, feedback, and adaptive difficulty within the rehabilitation activities also proved technically feasible. Throughout the evaluation, movement data acquired by the Kinect sensor were successfully reused by multiple system components simultaneously, including gameplay control, performance assessment, posture monitoring, and difficulty adaptation. This reduced the need for separate assessment procedures and demonstrated that a single motion-capture pipeline can support several rehabilitation functions concurrently.

The implementation of computational assessment based on selected **FMA-UE** and **WMFT** components revealed both advantages and limitations. On one hand, the framework enables movement-related information to be collected continuously throughout rehabilitation rather than only during occasional clinical assessments. On the other hand, the evaluation reinforced the fact that many clinically relevant characteristics, such as movement quality, coordination, and compensatory strategies, are difficult to fully represent using a limited set of kinematic variables. Consequently, the proposed assessment framework should be viewed as a tool for continuous performance monitoring rather than a replacement for clinician-administered evaluation.

The adaptive difficulty framework also produced encouraging observations. Participants generally reported that the exercises provided an appropriate level of challenge, suggesting that the

selected adaptation strategy was sufficient to prevent tasks from becoming either excessively easy or unnecessarily difficult during testing. However, the evaluation was performed using healthy volunteers whose movement performance was relatively consistent. Stroke survivors typically exhibit greater variability in motor control, fatigue, and day-to-day performance. As a result, the true effectiveness of the adaptation mechanism can only be determined through future clinical studies.

Several design decisions intended to support clinical usability also appeared beneficial. The Rehab Sequence Editor and therapist-management tools separate rehabilitation content from software implementation, allowing exercises and rehabilitation programs to be modified without changing the underlying application. Although these components were not formally evaluated by rehabilitation professionals, they address a practical limitation observed in many research-oriented rehabilitation systems, where therapists have limited control over exercise configuration and progression.

The multimodal feedback strategy similarly appeared to contribute positively to usability. Participants reported high ratings for instruction clarity and exercise comprehension, suggesting that the combination of visual guidance, audio cues, and posture-related feedback was generally effective in communicating task requirements. This is particularly relevant in rehabilitation environments, where misunderstandings regarding exercise execution can negatively affect both performance and assessment accuracy.

Overall, the evaluation indicates that the principal design decisions adopted during development contributed positively to the usability, flexibility, and functionality of the platform. More importantly, the study demonstrated that these components can operate together within a single rehabilitation environment while simultaneously revealing practical limitations that would likely not have been identified through isolated component testing. These findings provide confidence in the feasibility of the proposed architecture while highlighting specific areas requiring refinement before clinical deployment.

### 6.3 Technical Limitations Identified During the Evaluation

Additional limitations are associated with the Microsoft Kinect v2 sensor itself. Although Kinect provides reliable 3D skeletal tracking without requiring wearable sensors, its performance remains susceptible to temporary self-occlusion, rapid body movements, changes in body orientation, and variations in the relative position between the user and the sensor. The evaluation suggests that these tracking limitations affected different components of the platform to different degrees. While participants were generally able to complete the rehabilitation activities successfully, occasional tracking inaccuracies may have contributed to some of the posture-monitoring inconsistencies observed during testing and could also introduce variability into the kinematic measurements used for movement assessment and adaptive difficulty regulation. These observations indicate that the current tracking performance is sufficient for rehabilitation gameplay, but that improvements in sensing robustness would likely provide the greatest benefits for assessment reliability, compensation detection, and movement analysis. Future implementations may therefore benefit from

combining Kinect with complementary sensing technologies or more advanced pose-estimation algorithms to improve tracking robustness.

## 6.4 Limitations of the FMA-UE and WMFT Proxy Assessment Framework

### 6.4.1 Deviations from Clinical FMA-UE and Methodological Limitations

Although the proposed framework provides an automated and scalable proxy for upper-limb motor assessment, its translation from a clinician-administered examination to a markerless motion capture system introduces several methodological limitations and systematic deviations from the original **FMA-UE** protocol.

This approach introduces an inherent anthropometric bias, as absolute spatial thresholds do not account for inter-subject variability in body morphology, including torso depth, body mass distribution, and segment proportions. Consequently, individuals with different anthropometric characteristics may exhibit equivalent functional performance while achieving different proxy scores. A potential mitigation strategy would involve normalizing spatial thresholds relative to subject-specific trunk dimensions estimated during calibration.

Threshold values were selected based on the movement requirements described in the original **FMA-UE** protocol and adapted to account for the measurement capabilities and practical constraints of Kinect-based motion capture within the rehabilitation environment. For assessment items that do not possess a direct quantitative equivalent in the clinical scale, heuristic thresholds were defined to provide meaningful score separation while maintaining robustness to Kinect measurement noise. As the proposed framework was designed as a kinematic proxy rather than a validated clinical assessment tool, the selected thresholds should be interpreted as engineering approximations of the corresponding clinical criteria.

Furthermore, the accuracy of the proposed assessment is inherently constrained by the performance of Kinect v2 skeletal tracking. Joint position estimates may be affected by depth-sensing noise, temporary tracking loss, self-occlusion, and inaccuracies in anatomical joint localization. These limitations are particularly relevant during movements involving reach-behind-body postures, such as Item IV-A, where portions of the upper limb may become partially occluded from the sensor. Consequently, the reliability of the derived kinematic variables is dependent on the quality of the underlying skeletal tracking data.

A further deviation from the clinical **FMA-UE** arises from the scoring methodology itself. Whereas the original assessment evaluates the ability to perform specific movements under clinician supervision and considers both movement quality and task consistency, the proposed framework adopts an opportunistic peak-based scoring strategy. For each assessment item, the highest level of performance achieved during gameplay is recorded and used for score computation. As a result, transient successful movements may contribute disproportionately to the final score

compared with clinician-administered assessment, where repeated and consistent performance is typically required.

In the clinical **FMA-UE**, the influence of compensatory strategies is incorporated implicitly through clinician observation and judgement. In contrast, the proposed framework explicitly quantifies compensation using a continuous Compensation Index ( $C_{\text{index}}$ ), which is subsequently used to penalize the final score. This design choice reflects the requirements of real-time rehabilitation systems, where continuous monitoring and feedback are prioritized over discrete trial-based assessment.

While the inclusion of a compensation penalty enables objective quantification of movement quality during gameplay, it also transforms the resulting metric from a purely impairment-based score into a hybrid measure reflecting both motor capacity and compensatory behaviour. Consequently, the final score should not be interpreted as a direct equivalent of the clinical **FMA-UE**, but rather as a composite indicator of functional performance and movement quality within the rehabilitation environment.

A key limitation of the proposed framework is the absence of formal clinical validation against therapist-administered **FMA-UE** and **WMFT** assessments. Although the implemented proxies are grounded in kinematic interpretations of the original scales and informed by literature on upper-limb biomechanics, no direct statistical comparison with clinical scoring was performed. As a result, the reported scores should not be interpreted as clinically equivalent to the original instruments. Instead, they are intended for within-system consistency and longitudinal tracking of motor performance changes over time.

Despite these methodological limitations, the proposed framework demonstrates that clinically inspired movement assessment can be integrated directly within rehabilitation exercises using markerless motion capture. Unlike conventional clinical assessments, which are typically performed intermittently, the framework enables movement-related metrics to be generated continuously throughout rehabilitation sessions. Although the resulting scores cannot replace therapist-administered **FMA-UE** evaluations, they may provide valuable information regarding day-to-day performance variability, rehabilitation progression, and movement trends that would otherwise remain unobserved between formal clinical assessments.

#### 6.4.1.1 Limitations of the WMFT Proxy Assessment Framework

The proposed framework should be interpreted as a Kinect-based proxy of selected **WMFT** outcomes rather than a direct implementation of the clinical **WMFT** assessment.

The threshold values used to assign **FAS** scores are heuristic approximations derived from literature-informed task requirements and system testing rather than formal clinical calibration. Consequently, the resulting scores should be regarded as estimates of functional performance rather than clinically validated **FAS** ratings.

Furthermore, all **WMFT** proxy items use a common task completion duration when calculating the temporal component of the score. Unlike the original **WMFT** protocol, where each task is

timed independently, differences in execution speed between individual tasks are therefore not represented to the same extent within the proposed framework.

The framework primarily evaluates peak kinematic performance, including maximum joint angles and maximum reach distances. As a result, movement smoothness, tremor, synergistic coupling, corrective sub-movements, trajectory irregularity, and other qualitative movement characteristics typically considered by trained clinicians are not directly represented within the proxy score.

In addition, the forward-reaching metric corrects for trunk displacement to isolate upper-limb motion. While this approach improves estimation of arm-specific reaching ability, it differs from clinical **WMFT** scoring, where compensatory trunk movements may contribute to an evaluator's judgement of movement quality.

Finally, Kinect v2 skeletal tracking is subject to depth-estimation error, self-occlusion, and joint-localisation uncertainty. Although joint trajectories are filtered prior to analysis, residual measurement error may influence the extracted kinematic features and associated proxy scores.

## 6.5 Summary

The discussion presented in this chapter highlights both the strengths and limitations of the proposed rehabilitation platform. The results demonstrate the technical feasibility of integrating rehabilitation exercises, movement assessment, adaptive difficulty regulation, compensatory movement monitoring, and therapist-guided configuration within a single Kinect-based rehabilitation environment. The preliminary evaluation further showed that users were generally able to interact with the platform successfully and perceived the rehabilitation activities as usable, engaging, and easy to understand.

At the same time, the evaluation identified several areas requiring further refinement. Workspace personalization, posture-monitoring reliability, and the limitations associated with Kinect-based motion tracking illustrate the challenges of translating rehabilitation concepts into practical real-time systems. Similarly, the proposed **FMA-UE** and **WMFT** assessment frameworks provide continuous movement-related information during rehabilitation but remain computational proxies that require formal clinical validation before any relationship with established clinical outcome measures can be determined.

Taken together, the findings suggest that the principal challenges facing the proposed platform are no longer related to the integration of its core components, but rather to improving personalization, assessment robustness, and clinical applicability. Consequently, the work presented in this thesis establishes a functional and extensible foundation for future clinical studies involving stroke survivors while identifying specific technical and methodological areas that should be addressed in subsequent development stages.



## Chapter 7

# Conclusion and Future Work

### 7.1 Conclusion

This thesis presented the design, implementation, and preliminary evaluation of a Kinect-based serious game platform for upper-limb stroke rehabilitation. The proposed system integrates rehabilitation exercises, movement assessment, adaptive difficulty regulation, compensatory movement monitoring, therapist-guided configuration, and patient management within a single rehabilitation environment.

The results demonstrated the technical feasibility of combining these components into a unified framework capable of supporting real-time rehabilitation activities. The preliminary evaluation further showed that participants were able to use the platform successfully and perceived the rehabilitation activities as engaging, understandable, and suitable for rehabilitation purposes. Equally important, the evaluation identified several technical limitations, including challenges related to workspace personalization, posture-monitoring reliability, and the constraints of Kinect-based motion tracking. These findings provided valuable insight into aspects of the system requiring refinement before clinical deployment.

A key outcome of this work is the demonstration that movement assessment, adaptive rehabilitation, and therapist supervision can be integrated directly within rehabilitation gameplay rather than implemented as separate processes. While the proposed FMA-UE and WMFT frameworks remain computational proxies requiring clinical validation, they illustrate how clinically inspired movement assessment can be embedded within rehabilitation exercises to provide continuous performance information throughout therapy.

Overall, this thesis establishes a functional and extensible technological foundation for future rehabilitation research. Although clinical effectiveness has not yet been demonstrated, the results indicate that the proposed architecture is sufficiently mature to support further development and clinical evaluation involving stroke survivors.

## 7.2 Future Work

Although the proposed platform represents a comprehensive rehabilitation framework, several opportunities exist for further development and validation.

The highest priority is the clinical evaluation of the platform with stroke survivors. Such studies are necessary to determine the clinical relevance of the proposed movement-assessment framework, the effectiveness of the adaptive difficulty algorithm, and the overall therapeutic value of the rehabilitation games. Clinical evaluation should also investigate patient adherence over longer intervention periods and compare rehabilitation outcomes with those obtained using conventional therapy or existing rehabilitation technologies.

The computational movement-assessment framework developed in this thesis should also be validated against standardized clinical assessments administered by rehabilitation professionals. Establishing the relationship between the proposed kinematic indicators and established instruments such as the **FMA-UE** and **WMFT** would provide evidence regarding their suitability for supporting objective longitudinal monitoring in clinical practice.

Several technical improvements were identified during the preliminary evaluation. Future versions of the platform should incorporate individualized workspace estimation to ensure that interactive objects remain within each patient's functional reaching capacity. During discussions with a practising physiotherapist, an alternative adaptation strategy was identified in which rehabilitation tasks would initially be constrained to a comfortable range of motion and progressively expand as patient performance improves. Such an approach more closely reflects conventional rehabilitation practice, where therapists gradually increase movement demands as motor function recovers. Future work should therefore investigate adaptive workspace expansion mechanisms that dynamically adjust reaching boundaries according to longitudinal patient performance rather than relying exclusively on a calibration procedure performed regularly. Similarly, the posture monitoring algorithm should be refined through more robust personalization strategies capable of accommodating differences in body morphology, movement patterns, and environmental conditions while reducing false corrective feedback.

Although participants generally considered the rehabilitation difficulty appropriate, these findings should be interpreted cautiously because the evaluation involved healthy volunteers. Stroke survivors typically exhibit substantially greater variability in motor performance, fatigue, compensatory movement strategies, and recovery progression. Consequently, future work should investigate whether the proposed adaptive difficulty framework appropriately regulates rehabilitation challenge across different impairment levels or whether additional patient-specific adaptation strategies are required.

Future research could also investigate more advanced sensing technologies. While the Microsoft Kinect v2 provides reliable markerless **3D** motion tracking at relatively low cost, newer markerless pose-estimation frameworks based on computer vision and deep learning, as well as multimodal sensing approaches combining depth cameras, inertial sensors, or wearable devices, may improve tracking robustness while preserving accessibility for home-based rehabilitation.

Another promising direction involves expanding the rehabilitation content available within the platform. Additional serious games targeting different motor functions, bilateral coordination, activities of daily living, or cognitive rehabilitation could further increase exercise variety while supporting more comprehensive rehabilitation programmes. Likewise, the rehabilitation sequence editor could be extended to incorporate more sophisticated exercise scheduling strategies, automatic protocol generation, and data-driven personalization based on long-term patient progression.

Finally, the proposed architecture provides opportunities for broader clinical integration. Future implementations could support interoperability with electronic health record systems, cloud-based therapist dashboards, remote rehabilitation services, and artificial intelligence techniques capable of predicting patient progression and recommending personalized rehabilitation programmes based on accumulated longitudinal data.

In summary, this dissertation establishes a solid technological foundation for the development of adaptive serious game-based rehabilitation systems that combine objective movement assessment, therapist-guided personalization, and engaging rehabilitation experiences within a unified closed-loop framework. Continued engineering refinement together with rigorous clinical validation will determine the extent to which this approach can contribute to improving the accessibility, effectiveness, and personalization of post-stroke upper-limb rehabilitation.

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## Appendix A

# Questionnaire Used in the Usability Study

This appendix presents the questionnaire administered to the nine healthy volunteers who participated in the preliminary evaluation of the serious game platform developed for upper-limb rehabilitation after stroke. The questionnaire was designed to assess usability, user experience, exercise understanding, perceived usefulness, and overall satisfaction with the platform and its individual games.

### A.1 Participant Information

- Age: \_\_\_\_\_
- Gender: \_\_\_\_\_
- Previous experience with video games?    ☐ Yes    ☐ No
- Previous experience with motion-capture systems (e.g., Kinect)?    ☐ Yes    ☐ No

### A.2 Instructions

Please indicate your level of agreement with each statement using the following 5-point Likert scale:

- 1 – Strongly disagree
- 2 – Disagree
- 3 – Neither agree nor disagree
- 4 – Agree
- 5 – Strongly agree

### A.3 Usability and Interaction

| Statement                                                                         | 1                        | 2                        | 3                        | 4                        | 5                        |
|-----------------------------------------------------------------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| The system was easy to use.                                                       | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |
| The calibration process was easy to perform.                                      | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |
| My movements were accurately recognized by the system.                            | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |
| The instructions provided during the exercises were clear and easy to understand. | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |

### A.4 Exercises and Feedback

| Statement                                                                     | 1                        | 2                        | 3                        | 4                        | 5                        |
|-------------------------------------------------------------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| The exercises were easy to understand.                                        | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |
| The difficulty level of the exercises was appropriate.                        | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |
| The feedback provided by the system helped me improve my performance.         | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |
| The automatic adaptation of exercise difficulty matched my performance level. | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |

### A.5 Virtual Environment and Motivation

| Statement                                            | 1                        | 2                        | 3                        | 4                        | 5                        |
|------------------------------------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| The virtual environment was visually appealing.      | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |
| The games kept me motivated throughout the session.  | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |
| The variety of games enhanced my overall experience. | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |

### A.6 Overall Evaluation

| Statement                                                                           | 1                        | 2                        | 3                        | 4                        | 5                        |
|-------------------------------------------------------------------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| I believe this platform could be useful for upper-limb rehabilitation after stroke. | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |
| Overall, I had a positive experience using the platform.                            | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |
| I would recommend this platform for rehabilitation purposes.                        | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |

### A.7 Game Evaluation

Please rate your overall satisfaction with each game.

| Game                 | 1                        | 2                        | 3                        | 4                        | 5                        |
|----------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| Imitation Game       | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |
| Object Catching Game | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |
| Capsules Game        | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |
| Window Cleaning Game | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |

## A.8 Open-Ended Questions

1. Which game did you enjoy the most? Please explain your answer.
2. Which game did you enjoy the least? Please explain your answer.
3. Did you experience any difficulties while using the platform? If so, please describe them.
4. What improvements would you suggest for the platform or games?
5. Additional comments