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Smart technologies for motor function assessment in innovative and collaborative environments

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Abstract

Smart technologies are rapidly reshaping healthcare and industrial domains, creating environments where humans interact with virtual systems and collaborative robots. These innovations promise efficiency, rehabilitation opportunities, and enhanced safety, yet they also raise critical questions about ergonomics, cognitive load, and human adaptability. Despite the growing presence of virtual reality and robotics in several contexts, systematic and quantitative investigations into their impact on motor function and cognitive states remain limited. Addressing this gap, the present thesis explores how technologically enhanced environments influence human motor behavior, with the goal of informing the design of systems that are safe, effective, and human-centered. Human movement analysis has long been a cornerstone of clinical practice, rehabilitation, ergonomics, and performance research, but traditional methods often lack sensitivity and objectivity. Recent advances in wearable sensors, motion capture, electromyography, and immersive technologies now allow continuous, multidimensional, and high-resolution monitoring of motor behavior. This thesis leverages these innovations to investigate motor strategies, workload, and postural control in contexts where humans collaborate with technologically mediated environments.

The experimental core comprises four complementary studies: *(1)* the detection of sensorimotor deficits in individuals with dementia during reaching and catching tasks in virtual reality environments; *(2)* the analysis of postural control in collaborative manipulation with a robotic arm; *(3)* the multimodal investigation of a hand-over task involving robotic interaction and stop signals; and *(4)* the development of electromyography-based machine learning models to classify reaching targets and infer upper-limb motor intentions. Together, these studies integrate kinematic, postural, muscular and cognitive-related data to characterize key aspects of human adaptation in innovative and collaborative environments.

The findings demonstrate that: virtual reality assessments can sensitively detect motor alterations associated with dementia; robot-assisted tasks modulate motor and cognitive strategies; electromyography-driven models can reliably predict reaching targets, with accuracy depending on muscle selection, feature extraction, and temporal windows. Beyond methodological contributions, the results have practical implications: they support early diagnosis and rehabilitation in neurodegenerative conditions, inform ergonomic risk assessment and adaptations in industrial robotic collaboration, and lay the groundwork for adaptive robotic systems capable of responding to human intention in real time. Collectively, these results advance the understanding of human adaptation in innovative and collaborative environments. By bridging neuroscience, ergonomics, and robotics, this thesis contributes to the broader effort of integrating intelligent technologies into healthcare and industry in ways that aim to support human performance and collaboration.

Contents

List of Abbreviations

AD	Alzheimer's Disease
AP	Anterior-Posterior
BT	Bagged Tree
CE-AREA	95% Confidence Ellipse Area
COP	Center of Pressure
DET	Determinism
EMG	Electromyography
F	Free
GLMM	Generalized Linear Mixed Models
HC	Healthy Controls
HRC	Human-Robot Collaboration
IMU	Inertial Measurement Unit
KNN	k-Nearest Neighbors
LDA	Linear Discriminant Analysis
LED	Light-Emitting Diode
LOSO	Leave-One-Subject-Out
MCI	Mild Cognitive Impairment
MDIST	Mean Distance
ML	Medial-Lateral
MMSE	Mini-Mental State Examination
MSD	Musculoskeletal Disorder
MVEL	Mean Velocity
REC	Recurrence Rate
RF	Robot Free
RP	Robot Plane
RQA	Recurrence Quantification Analysis
sEMG	Surface Electromyography
SVM	Support Vector Machine
SW-AREA	Sway Area
TMCf	Time-Varying Multi-Muscle Coactivation Function
TTn	Trial Type n (n = 0, 1, 2, 3, 4, 5)
VR	Virtual Reality

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Introduction

1.1 Context and rationale

Human movement analysis aims at gathering quantitative information about the mechanics of the musculoskeletal system during the execution of a motor task [1]. Motor function encompasses a wide range of abilities, including coordination, strength, dexterity, balance, and postural control. The assessment of motor function is a fundamental aspect of clinical practice, rehabilitation, ergonomics, and human performance research, as it provides insights into an individual's functional capacity, mobility, and overall health.

Traditional methods for evaluating motor function include clinical scales, observational assessments, and standardized performance tests. These approaches, while informative and widely used, present several limitations. They are often subjective, reliant on the evaluator's experience, and may lack the sensitivity to detect subtle changes in motor performance. Moreover, many traditional assessments are episodic, providing only a snapshot of performance rather than capturing continuous or dynamic changes over time.

Recent technological advancements have opened new avenues for the objective and high-resolution assessment of human movement, through the integration of smart technologies. In recent years, the term "smart" has been widely used to describe digital technology initiatives across various domains [2]. This term denotes the integration of advanced digital solutions into intelligent systems. They include wearable sensors, motion capture systems, force platforms, virtual reality environments, robotics, and artificial intelligence. They enable researchers to capture detailed information about motor behavior with unprecedented accuracy. For example, wearable inertial measurement units (IMUs) can track joint kinematics in real-time, electromyography (EMG) sensors provide detailed insights into muscular activation patterns, eye-tracking devices quantify attentional load and cognitive engagement, and force sensors can assess postural control and balance.

Unlike traditional methods, which often rely on subjective observations or limited measurement tools, these technologies offer enhanced objectivity, continuous monitoring, and the ability to analyze complex, multidimensional aspects of human movement. They enable repeatable, adaptable, and scalable evaluations. Additionally, they support personalized assessment and intervention strategies, bridging the gap between laboratory research and real-world applications. Such approaches not only enhance the accuracy and reproducibility of motor assessments but also facilitate the investigation of subtle changes in motor performance due to aging, neurological disorders, rehabilitation, or interactions with collaborative technologies, including robotic systems. This allows for richer insights into human movement, interaction, and engagement with the environment.

Smart technologies are reshaping how we live, work, and receive care, transforming human interaction with the surrounding environment. Since the Industrial Revolution, technological progress has continuously reshaped the relationship between people and their surroundings [3], to the point that it now permeates virtually every aspect of human life [4]. Today, we are experiencing an accelerated process of digitization, observable both in daily life and in the workplace, where the virtualization of spaces has become an increasingly relevant and widely debated issue [5]. Consequently, these technologies have moved beyond experimental laboratories and are actively reshaping multiple domains [2]. In particular, the impact of smart technologies is especially pronounced in contexts that demand high precision and responsiveness: in healthcare, they enable more accurate and personalized treatments while alleviating clinical workload; in industrial settings, they support automation and enhance collaboration between humans and machines/robots. Although the healthcare and industrial contexts differ in their immediate goals, they share important similarities: both require technologies that can integrate seamlessly into human tasks, provide precise, objective measurement of motor performance, support safe and effective interaction between humans and machines, and be adaptable to individual abilities and environmental constraints.

Although smart technologies hold great promise to improve efficiency, productivity, and safety, their adoption also raises important questions regarding impacts on communities, the environment, and the economy [2]. Their integration into collaborative and innovative environments remains still underexplored. This thesis is situated within this emerging research area, focusing on the use of smart technologies for motor function assessment in healthcare and industrial settings. Specifically, it examines four complementary studies: *(i)* sensorimotor analysis in Alzheimer's patients using virtual reality; *(ii)* postural analysis of human participants interacting with a collaborative robot, *(iii)* multimodal assessment of human–robot collaboration combining postural, kinematic, muscular, and cognitive measures; and *(iv)* EMG-based machine learning models to classify upper-limb motor intentions in reaching tasks. Together, these studies aim to advance both methodological and applied knowledge, illustrating how smart technologies can be harnessed to evaluate human motor performance in innovative and collaborative environments, with implications for healthcare, ergonomics, and human–robot interaction.

1.2 Aim of the thesis

The primary aim of this thesis is to investigate the integration of smart technologies in healthcare and industrial contexts where human performance, safety, and well-being are critical. Through a series of controlled experimental studies, this research examines how emerging technologies can contribute to motor function assessment and human–technology interaction – from using Virtual Reality (VR) for neurodegenerative diagnosis and rehabilitation, to evaluating the effects of Human–Robot Collaboration (HRC) on workers' physical and cognitive states, and developing methods to predict upper-limb movement direction as a foundation for adaptive robotic control. The methodological framework combines multiple measures, enabling a comprehensive and quantitative characterization of human performance and interaction across diverse contexts. Although virtual reality and robotic systems could be applied across a wide range of domains, this thesis focuses specifically on healthcare and industrial contexts due to their experimental feasibility, the availability of established methodological frameworks, and the relevance of the challenges they address. Nevertheless, potential extensions – such as VR in industrial settings or HRC in clinical scenarios – are acknowledged as promising directions for future research.

Beyond the specific application domains, this thesis is guided by a broader research question: how human motor behavior adapts when individuals interact with technologically mediated environments, that could alter sensory feedback, task demands, or interaction dynamics. In this perspective, smart technologies are not merely tools for assistance or measurement but are conceptualized as structured experimental perturbations that elicit and make observable mechanisms of motor and cognitive adaptation.

The central hypothesis of this thesis is that human behavior in technologically mediated environments is inherently adaptive, and that this adaptation can be quantitatively characterized as a multidimensional process integrating kinematic, postural, neuromuscular, and cognitive domains. Within this framework, smart technologies act as structured experimental perturbations targeting different levels of the human motor system. Each experimental paradigm, in turn, addresses a distinct and complementary level of human motor behavior: sensorimotor (VR-based assessment in neurodegenerative populations), interactional (human–robot interaction in collaborative tasks), and neuromuscular (EMG-based decoding of motor intentions). Together, these levels provide a unified multidimensional characterization of adaptive motor behavior, spanning from perception–action integration to interpersonal coordination and motor command generation. By systematically analyzing the adaptive responses elicited across different technological settings, this thesis aims to advance the understanding of human motor behavior as a multidimensional process emerging from the interaction between the individual and technologically mediated environments.

Overall, this thesis offers a comprehensive exploration of how smart technologies can be leveraged not only to assess human motor function, but also to reveal the underlying adaptive mechanisms that govern behavior in complex environments. By combining rigorous quantitative methods with ecologically valid experimental paradigms, it provides evidence-based strategies for improving rehabilitation, task execution, and ergonomic design, contributing to both scientific understanding and practical applications.

1.3 Structure of the thesis

The remainder of this dissertation is structured as follows:

- Chapter 2 provides a comprehensive state-of-the-art overview of smart technologies for motor function assessment and their applications in innovative and collaborative environments. It outlines the main sensor-based approaches for quantitative motor evaluation – including motion tracking, force and pressure sensing, electromyographic, and eye-tracking systems – and examines how emerging tools such as virtual reality and robotics are reshaping clinical and industrial assessment practices.
- Chapter 3 explores sensorimotor impairments in individuals with Alzheimer's Disease, Mild Cognitive Impairment, and age-matched healthy controls during reaching and catching tasks performed in immersive virtual reality environments. The study aims to identify quantitative kinematic markers sensitive to early neurodegenerative changes, demonstrating how virtual reality can serve as a powerful diagnostic and rehabilitative tool for assessing motor and cognitive decline.
- Chapter 4 examines the effects of Human–Robot Collaboration on human performance in industrial contexts through two complementary studies. The first focuses on postural control during collaborative manipulation tasks, using both linear and nonlinear metrics derived from center of pressure dynamics to quantify ergonomic risk and postural adaptation. The second adopts a multimodal approach combining postural, kinematic, muscular, and cognitive eye-tracking data to characterize the interplay between physical effort, cognitive demand, and coordination strategies in collaborative settings.
- Chapter 5 investigates the key factors influencing EMG-based classification of upper-limb reaching movements, with the final aim of designing EMG-driven adaptive assistive robotic technologies. It examines how time-window length, muscle selection, feature configuration, classifier type, and validation strategy affect the accuracy of predicting movement intention.
- Chapter 6 concludes the dissertation by summarizing the main findings, discussing their broader implications in healthcare and industrial domains, and outlining limitations and perspectives for future research and technological development.

2

Background

This chapter is structured to provide a comprehensive background and state-of-the-art overview of smart technologies for motor function assessment and their applications in innovative environments.

Section 2.1 outlines the main technological approaches used for the quantitative assessment of motor function. It presents the principles, advantages, and limitations of the primary sensor-based systems currently employed in research and applied settings, including force and pressure sensing systems (2.1.1), motion tracking technologies (2.1.2), electromyographic acquisition techniques (2.1.3), and eye-tracking technologies (2.1.4).

Section 2.2 focuses on the applications of these technologies in innovative and collaborative contexts, examining how emerging systems such as virtual reality platforms, robotic devices, and Human–Robot Collaboration frameworks are reshaping the assessment and enhancement of motor performance. The section is further divided into two subsections: the first (2.2.1) discusses applications in healthcare, emphasizing diagnostic, rehabilitative, and therapeutic uses, while the second (2.2.2) explores industrial applications, with particular attention to ergonomics, human–robot interaction, and collaborative workspaces.

This chapter aims to delineate the current technological landscape in motor function assessment, illustrating how smart systems contribute to more precise, objective, and context-aware evaluations across diverse domains.

2.1 Smart technologies for motor function assessment

Motor function – the ability to plan, control, and execute movements – is a cornerstone of human health and performance. Accurate assessment of motor function is essential for understanding the progression of neurological and musculoskeletal disorders, designing effective rehabilitation protocols, and optimizing human performance in both clinical and occupational settings. Traditional motor assessments, although clinically useful, often rely on subjective observation or coarse scoring systems, limiting their sensitivity and objectivity. In recent years, advances in smart technologies – ranging from wearable sensors to robotics and virtual reality – have enabled precise, real-time, and multidimensional evaluation of motor performance. The integration of smart technologies into motor function assessment is transforming the landscape, offering more accurate, real-time, and context-aware evaluations. The following sections present an overview of the main technologies currently used for motor function assessment, outlining their principles, applications, and relevance across healthcare and industrial domains.

2.1.1 Force and pressure sensing technologies

Force and pressure sensors are fundamental tools in biomechanics and ergonomics, as they allow the detection and quantification of mechanical interactions between the human body and the surrounding environment. These systems rely on different transduction mechanisms – such as piezoelectric, capacitive, or resistive elements – that convert mechanical deformation into electrical signals proportional to the applied force [6].

Force plates measure ground reaction forces in three orthogonal directions (vertical, anterior-posterior, and medial-lateral) and represent one of the most reliable and widely adopted tools for assessing human balance, postural control, and movement dynamics [7]. The mechanism of force plates is based on four load cells placed at the corners of an outer plate, providing the ability to measure the force induced by a subject moving on the plate, without the need for direct visibility of the subject or for the placement of active attachments on their body [8]. By measuring the ground reaction forces (including their magnitude, direction, and point of application), force platforms allow for precise computation of biomechanical variables such as the center of pressure (COP), moments of force, and loading distribution across the base of support [9]. The COP trajectory derived from force plate data provides a sensitive index of postural stability and neuromuscular control, capturing both the amplitude and temporal structure of sway behavior [10], [11]. In both static and dynamic conditions, the analysis of ground reaction forces enables researchers to characterize underlying control strategies, assess sensorimotor integration, and identify compensatory mechanisms adopted during balance maintenance [12], [13]. Force plate assessments are thus fundamental in biomechanics, motor control, and clinical research, supporting investigations into age-related changes in balance [14] and rehabilitation outcomes [15]. Their high temporal resolution also makes them suitable for dynamic tasks, such as gait, jumping, or object manipulation, where rapid shifts in COP and force profiles reflect the coordination between lower-limb and trunk musculature [16], [17].

Pressure sensors capture localized pressure distributions at the body–surface interface and are widely employed to assess plantar load, contact patterns, and weight distribution during both static and dynamic tasks [18], [19]. These sensors can be embedded in insoles, mats, or wearable devices to provide high-resolution spatial and temporal information about foot–ground interactions, allowing for detailed analysis of postural stability, gait characteristics, and load asymmetries [20]. Plantar pressure mapping enables the quantification of parameters such as peak pressure, pressure–time integrals, and contact area, which are critical for understanding locomotor strategies, balance control, and the mechanical function of the lower limbs [8], [21]. Advances in sensor miniaturization and flexible electronics have facilitated the integration of pressure measurement systems into wearable platforms, enabling real-time monitoring of gait and posture in both laboratory and ecological settings [19]: these wearable systems are increasingly used in sports science, clinical diagnostics, and rehabilitation to evaluate foot mechanics, detect abnormal loading patterns, and track recovery following injury or surgery [20]. Moreover, pressure-based assessments complement force plate analyses by offering distributed measurements over the plantar surface, providing insights into regional load redistribution, dynamic balance strategies, and compensatory behaviors in various populations [18]. Overall, pressure-sensing technologies offer a versatile and accessible means to investigate human postural and locomotor function, bridging the gap between laboratory-grade instrumentation and wearable, real-world monitoring systems.

The main strength of these technologies lies in their ability to provide direct, objective, and high-resolution measurements of physical forces and pressure distributions, thereby enabling a quantitative assessment of motor performance, balance control, and functional recovery [19], [20]. By converting mechanical interactions between the human body and the environment into measurable data, force plates and pressure sensors support accurate evaluation of kinetic parameters and load transfer mechanisms at the basis of postural stability and movement coordination [11].

Despite these advantages, several limitations constrain their applicability. Spatially constrained systems such as force plates, while offering high precision and reliability, restrict natural movement patterns to confined laboratory environments and are unsuitable for continuous or ecological monitoring [7], [22]. Their setup requirements and limited portability make them less practical for field studies or real-world applications. Conversely, wearable pressure and inertial sensors provide greater flexibility and mobility, allowing long-term tracking of gait and posture in everyday contexts, but are subject to challenges such as signal drift, sensor misalignment, temperature sensitivity, and calibration errors, which can affect data accuracy and repeatability [19], [23]. Furthermore, variations in sensor placement, material compliance, and inter-subject differences may introduce biomechanical and technical variability, complicating the comparison of results across studies [24], [25]. Ongoing research is thus focused on hybrid systems and advanced signal-processing techniques that combine the robustness of laboratory-grade instrumentation with the ecological validity of wearable solutions, aiming to enhance measurement reliability while preserving natural movement conditions [26]. Moreover, integrating force and pressure sensors with inertial measurement units, electromyography, or optical motion capture systems enables a more comprehensive understanding of human biomechanics, combining kinetic, kinematic, and muscular information within a unified framework [27], [28].

2.1.2 Motion tracking technologies

Motion tracking technologies, including optical motion capture systems and Inertial Measurement Units (IMUs), represent foundational tools in the quantitative assessment of human movement, providing accurate, objective, and reproducible measures of kinematic behavior [29], [30], [31], [32]. These systems have become integral to biomechanics, clinical gait analysis, ergonomics, and motor control research [33], [34], [35], [36] – where precise characterization of body motion is essential for understanding performance, diagnosing impairments, or evaluating interventions.

Optical motion capture systems are among the most accurate and widely adopted technologies for quantifying human movement. These systems employ multiple high-speed cameras to track the position of reflective or active markers placed on anatomical landmarks of the body, allowing for the three-dimensional reconstruction of motion through triangulation algorithms [1], [37], [38], [39]. Usually, markers are positioned following standardized biomechanical models – such as the Plug-in Gait or Helen Hayes protocols [40], [41]. Two main types of optical systems can be distinguished: passive systems utilize passive reflective markers that are illuminated by infrared light , while active systems employ light-emitting diodes (LEDs) that generate their own signal, providing improved robustness in environments with variable illumination [42]. The reconstructed trajectories are then processed through biomechanical modeling to compute joint kinematics, enabling detailed quantitative analyses of human motion [43]. Due to their high spatial and temporal resolution, optical motion capture systems have become the gold standard for human motion analysis [44]. Nevertheless, several limitations constrain their applicability: the accuracy of optical systems depends strongly on the quality of camera calibration, marker placement, and the maintenance of a clear line of sight between markers and cameras [45]; occlusions, soft tissue artifacts, or mislabeling can introduce errors in the reconstructed trajectories [46]; the complexity and cost of the setup, as well as its reliance on controlled laboratory conditions, limit the ecological validity of the captured movements [47], [48]. Recent advances in markerless motion capture and computer vision-based methods have begun to address these challenges: using deep learning and multi-view reconstruction algorithms, these systems can extract human motion directly from video data, reducing the need for physical markers while enabling more naturalistic analyses of movement [49], [50].

Inertial Measurement Units (IMUs) are wearable sensors widely used for motion analysis in biomechanics, sports science, rehabilitation, and ergonomics [51]. An IMU typically integrates accelerometers, gyroscopes, and magnetometers, allowing for the measurement of linear acceleration, angular velocity, and orientation of body segments in three-dimensional space [32], [52], [53]. IMUs provide several advantages over traditional optical motion capture systems: they are portable, lightweight, and relatively inexpensive, and can be used in unconstrained, real-world environments, enabling the study of natural movement outside the laboratory [54], [55], [56], [57]. Unlike optical systems, IMUs do not require a line of sight, making them robust to occlusions and suitable for long-term monitoring in daily activities or occupational settings [58]. However, despite these advantages, IMUs also have limitations. For instance, the integration of accelerometer and gyroscope signals over time can lead to drift errors, causing gradual inaccuracies in position and orientation estimation [52], [53], [54], [59], [60]. Additionally, soft tissue artifacts, sensor misplacement, and magnetic disturbances can affect measurement reliability, particularly in dynamic movements [61]. To mitigate these issues, sensor fusion algorithms are used to combine measurements from multiple sensors and improve accuracy [60], even though the trade-off between portability and absolute accuracy remains a central challenge in IMU-based motion tracking [62].

These technologies are extensively employed in a wide range of applications, including gait analysis, joint kinematics assessment, and postural control evaluation, where they provide quantitative and objective measures of motor performance, movement coordination, and biomechanical efficiency [43], [63], [64]. Through high-resolution motion data, optical motion capture and IMU-based systems enable detailed examination of spatiotemporal parameters, joint angles, segmental accelerations, and center-of-mass dynamics, supporting the assessment of locomotor stability and neuromuscular control strategies [54], [60]. In this context, the development of hybrid motion capture systems that combine optical and inertial sensing modalities offers a promising avenue for achieving comprehensive, robust, and adaptive motion analysis across a wide range of experimental and real-world scenarios.

2.1.3 Electromyographic acquisition technologies

Electromyography (EMG) is a widely used technique for measuring electrical activity generated in muscle fibers during voluntary or involuntary muscle contraction. This electrical activity reflects the summation of action potential generated by the depolarization and repolarization of muscle fiber membranes in response to neural stimulation.

EMG provides a direct and objective means of quantifying neuromuscular function, and it has become a cornerstone tool in both experimental and applied human movement research. Its applications span numerous disciplines, including movement analysis in sports and exercise science, ergonomic assessment in occupational health and safety, muscle fatigue and force estimation in physiology, myoelectric control for assistive and prosthetic devices, and the diagnosis and monitoring of neuromuscular disorders in clinical neurophysiology.

From a methodological standpoint, EMG signals can be recorded through two principal approaches: intramuscular electromyography and surface electromyography (sEMG) [65]. The selection between these techniques depends on several factors, including spatial selectivity, stability of signal acquisition, invasiveness, and susceptibility to noise or cross-talk [66].

Intramuscular-EMG involves inserting fine wire or needle electrodes directly into the muscle tissue, allowing for precise detection of action potentials from single motor units or small groups of fibers [67]. This approach yields highly specific and reliable data with excellent signal-to-noise ratio and temporal precision, making it especially useful in clinical diagnostics and research requiring detailed insight into motor unit behavior [67]. However, its invasive nature, relative discomfort to subjects, and limited suitability for dynamic or long-duration tasks have confined its use mostly to controlled laboratory and medical settings [68].

In contrast, sEMG offers a non-invasive alternative, recording the composite electrical activity of multiple underlying muscle fibers through electrodes on the skin surface. Although sEMG sacrifices the fiber-level resolution of intramuscular-EMG, it provides a broader view of muscle activation and coordination patterns across muscles or muscle groups [68]. Hence, sEMG is widely adopted in biomechanics, ergonomics, rehabilitation, sports science, and human–computer or human–robot interaction studies. The technique allows investigation of motor control strategies, intermuscular coordination, and neuromechanical coupling under both static and dynamic conditions [69].

Traditional sEMG setups typically employ bipolar electrode configurations, where the differential voltage between two closely spaced electrodes is amplified and recorded. While this configuration remains a gold standard in many contexts, recent advances in high-density surface electromyography have transformed the field by enabling spatial mapping of muscle activation with high resolution [70]. In high-density sEMG, arrays or grids of many electrodes densely sample the muscle surface, allowing decomposition of surface signals into individual motor unit action potentials and the identification of spatial activation patterns [71]. The improved spatial resolution and ability to infer motor unit behavior noninvasively represent a major methodological advancement [72].

In both conventional and high-density sEMG, signal quality depends heavily on the electrode–skin interface. Before sEMG acquisition, careful skin preparation is required to minimize impedance and reduce artifacts introduced by subcutaneous tissues, which act as low-pass filters and attenuate signal amplitude [73]. Standard procedures include hair removal or shaving, gentle abrasion of the skin, and cleansing with alcohol or conductive gel/paste to improve electrode contact [74]. These steps are critical for the reproducibility and reliability of EMG recordings, especially when comparing across sessions or subjects.

One of EMG's main strengths is its high temporal resolution, enabling real-time monitoring of muscle activation timing and dynamics. This allows detailed characterization of activation onset, coordination, recruitment order, and temporal patterns of motor control, making EMG a powerful tool in clinical gait and movement analysis, rehabilitation, sports science, and ergonomics for quantifying muscle demands and fatigue trends.

However, EMG data collection and interpretation have inherent challenges. EMG signals are sensitive to noise and artifacts from electrode motion, skin impedance changes, electromagnetic interference, and cross-talk between adjacent muscles [75]. Extracting meaningful information from raw EMG often requires advanced signal processing, including filtering, rectification, envelope extraction, and time–frequency or decomposition methods. Interpreting such processed signals demands expertise in signal analysis and physiological modeling, limiting ease of use for non-specialists [76].

Moreover, practical constraints related to EMG systems – such as subject comfort, mobility, and applicability outside laboratory settings – have driven technological innovations. Wireless and miniaturized EMG systems allow ambulatory wearable monitoring of muscle activity in real-life settings. Advances in flexible, stretchable noninvasive electrode designs improve comfort and stability of skin contact [77]. Integrative systems combining EMG with motion capture, inertial sensors, force plates, or other physiological signals enable multimodal analysis of neuromuscular function [78]. These trends are expanding EMG's applicability in prosthetic control, neurorehabilitation, sports analytics, ergonomics, and human–machine interfacing.

2.1.4 Eye-tracking technologies

Eye-tracking technologies provide an invaluable complement to traditional motor assessments by quantifying the perceptual and attentional mechanisms underlying task execution. By continuously monitoring eye movements, these systems enable the investigation of how visual information guides motor actions, revealing the cognitive strategies and attentional dynamics that accompany physical performance [79].

Eye-tracking devices capture parameters such as gaze direction, fixation location and duration, saccadic velocity, and pupil dilation, which together provide a detailed record of visual behavior [80]. These measurements are typically derived from infrared-based corneal reflection and pupil-center tracking, allowing for the estimation of gaze position relative to a display or scene [81]. Depending on the application, eye-tracking systems can be screen-based, suitable for controlled laboratory experiments, or head-mounted/wearable, enabling gaze tracking during naturalistic movements and interaction with physical environments [82]. The combination of spatial and temporal precision allows researchers to infer underlying cognitive states such as attention allocation, information processing, and workload [83].

Eye-tracking has become a key tool in cognitive and motor performance assessment, particularly for evaluating attentional focus, visual search strategies, and sensorimotor coordination in complex tasks [84], [85]. In cognitive ergonomics and human–computer interaction, gaze behavior provides insight into user experience, interface usability, and decision-making processes [86]. In clinical and rehabilitation contexts, eye-tracking contributes to the evaluation and retraining of visuomotor functions following neurological disorders such as stroke, Parkinson's disease, or traumatic brain injury [87], [88]. In sports science and occupational performance, gaze metrics are used to assess expertise, situational awareness, and cognitive workload under demanding conditions [89], [90]. Furthermore, in collaborative robotic environments, eye-tracking facilitates the analysis of human attention, intention prediction, and interaction fluency between humans and intelligent systems [91], [92].

The main advantages of eye-tracking technologies lie in their non-invasiveness, high temporal resolution, and ability to provide real-time insights into cognitive and perceptual states during task performance [93]. By quantifying gaze dynamics, eye-tracking enables objective assessment of attentional distribution, visual scanning patterns, and mental workload, complementing traditional kinematic and physiological analyses [94]. However, several limitations affect data accuracy and interpretability. Eye-tracking performance can be influenced by lighting conditions, head movements, calibration stability, and individual differences such as eye anatomy or the use of glasses [95]. Moreover, the inference of cognitive load or attention from gaze metrics requires careful consideration of task context and individual strategy, as gaze behavior does not always map directly onto cognitive effort [96].

Recent advancements are expanding the potential of eye-tracking for motor function assessment. The integration of eye-tracking with virtual and augmented reality environments allows for immersive and ecologically valid investigation of perceptual-motor behavior in complex or dynamic contexts [97]. Eye-tracking is also increasingly employed in dual-task paradigms, where simultaneous cognitive and motor demands are used to assess cognitive-motor interactions and attentional resource allocation [98], [99], [100]. Moreover, the fusion of eye-tracking with other sensing modalities – such as motion capture, EMG, and physiological monitoring – supports a multidimensional understanding of human performance, bridging perception, cognition, and action in a unified analytical framework [101], [102], [103], [104]. These developments position eye-tracking as a key component in next-generation smart assessment systems, capable of capturing the intertwined cognitive and motor aspects of human functions.

2.2 Applications in innovative and collaborative environments

Innovative and collaborative environments are increasingly shaping the way humans interact with technology across different domains, including healthcare and industrial contexts. In this thesis, the term "collaborative environments" refers broadly to technology-mediated settings in which humans interact with systems that can influence, support, or even adapt to human behavior. These environments may involve interaction with virtual agents or systems, as in virtual reality setups, or with physical robotic devices, as in human–robot collaboration scenarios. Despite their different application domains, these systems share common characteristics: they create structured interaction contexts, allow controlled manipulation of task conditions, and enable the acquisition of multimodal data to analyze human motor, cognitive, and behavioral responses.

Virtual Reality (VR) refers to interactive computer-generated environments that simulate real or imagined scenarios, offering immersive, controlled, and repeatable settings that replicate real-world tasks while allowing precise manipulation of variables. Enhanced by technologies such as motion capture sensors, eye-tracking systems, and haptic devices, VR enables detailed assessment of motor control, attention, and cognitive workload. By creating the perceptual experience of being physically present in a synthetic 3D space, VR allows users to engage with virtual environments and characters, enhancing immersion and facilitating meaningful interactions [105]. Its programmable nature makes it possible to design specific tasks, adjust difficulty, manipulate sensory cues, and record user responses in real time, making VR an ideal tool for controlled experimentation, performance evaluation, and clinical applications. Moreover, VR offers the unique advantage of exposing individuals to a wide variety of situations [106] under safely controlled and repeatable conditions, with precise control over presented stimuli [107].

Robotic collaborative environments allow humans and robots to work synergistically, accomplishing tasks more efficiently than either could achieve alone. These collaborative settings are increasingly applied in manufacturing, logistics, and service robotics. Smart technologies enable robots to adapt to human behaviors, anticipate actions, and ensure safety through compliant interactions. Beyond industrial applications, robotics can support rehabilitation, with assistance adapting in real-time to a user's motor capabilities to provide tailored functional support.

Overall, smart technologies enhance both virtual reality and robotic environments by enabling adaptive, responsive, and data-driven interactions. A key application is motion analysis, where several technologies allow detailed monitoring of movement, posture, neuromuscular control, and cognitive attention, supporting ergonomic assessment and personalized feedback.

2.2.1 Healthcare applications

The recent exponential growth of metaverse technology has been instrumental in reshaping a myriad of sectors, not least digital healthcare [108]. Smart technologies are increasingly transforming healthcare, offering innovative tools to support diagnosis, monitoring, and rehabilitation [109]. Digital systems such as wearable sensors, robotics, and VR provide clinicians with objective and reproducible measures that go beyond the limitations of traditional assessments, which often rely on subjective observation and may lack sensitivity to subtle or early impairments. These approaches open new opportunities for personalized and data-driven interventions. They further expand the toolkit available to clinicians, enabling more personalized and effective treatment strategies.

Among these emerging technologies, VR is rapidly gaining popularity in healthcare, as new technological breakthroughs enable diagnosis and therapy [110], [111] and offer transformative opportunities for patient care, medical education, and therapeutic interventions [112]. A key advantage of VR is its ability to provide fully interactive three-dimensional simulations of real-world environments and social situations, making it especially effective for cognitive and performance training, including the development of social and interaction skills [113]. Its flexibility enables researchers and clinicians to challenge both cognitive and motor functions in standardized yet engaging ways. Moreover, it enables multiple repetitions of simple tasks in a clinical setting, reducing the need for constant supervision by the medical staff, which could significantly lower the costs associated with training facilities [110]. This approach offers various advantages over traditional methods, such as adaptability to patient needs [114], friendly and motivating interaction, and automatic acquisition of performance-based information, showing effectiveness in improving motor functionality in patients with neurological disorders [115], [116]. Its immersive nature enhances participant engagement, which is essential for both assessment and rehabilitation [117], [118], [119], [120]. VR is valued for its ability to deliver repeatable and standardized stimuli, precisely capture kinematic and temporal data, and simulate ecologically valid scenarios while maintaining experimental control. As such, VR can act as both a diagnostic tool – revealing deficits in motor or cognitive function –

and a rehabilitation platform – providing targeted, adaptive training exercises. For example, in the field of neurorehabilitation, VR is beginning to be accepted as adjunctive therapeutic tool in the treatment of neurological patients, through real-time simulation and multiple sensorial channels, providing the opportunity to perform functional, repetitive, and rewarding activities [121]. Additionally, many clinical studies are now favoring VR-based intervention for motor function, balance, gait, and activities of daily living in patients with stroke [122]. However, despite all these advantages and the promising advancements in VR technologies within healthcare, there is still a missing full integration into established healthcare practices and there is limited empirical evidence evaluating their impact on patient adherence and treatment outcomes [112]. Therefore, more research is needed to understand the specific needs and preferences of healthcare professionals and patients when incorporating these technologies, as well as strategies to increase technological acceptance and usability in diverse healthcare environments [112].

In parallel, robotics is increasingly shaping the field of healthcare, offering innovative solutions for surgery, rehabilitation, patient assistance, and telemedicine. For example, surgical robots enhance precision, dexterity, and visualization, allowing surgeons to perform minimally invasive procedures with reduced patient trauma and faster recovery times [123]. In rehabilitation, robotic devices provide repetitive, task-specific training tailored to individual patient needs [114]. Exoskeletons and robotic-assisted gait trainers support motor recovery in patients with neurological disorders such as stroke or spinal cord injury, enabling intensive and controlled therapy that would be difficult to achieve manually [124], [125], [126]. In this context, robots can also adapt in real-time to the user's performance, providing personalized assistance and resistance levels to optimize motor learning and neuroplasticity. Moreover, service robots assist healthcare staff and patients in daily activities, reducing physical strain on caregivers and enhancing patient autonomy. Telepresence robots and robotic monitoring systems further extend healthcare delivery, enabling remote consultations, continuous monitoring, and intervention in situations where direct human presence is limited [127], [128]. Overall, robotics in healthcare integrates precision, adaptability, and scalability, complementing traditional care methods and digital technologies such as VR. The combination of robotic systems with immersive technologies opens new avenues for rehabilitation, training, and patient engagement, facilitating more effective, personalized, and data-driven healthcare interventions.

Indeed, one recent trend in healthcare combines robotics and VR, harnessing the unique strengths of both technologies [129], [130]. Robotics provides precise, repeatable physical interventions, while VR offers immersive and customizable environments for cognitive and motor training. Together, they create synergistic, patient-centered interventions that enhance both physical and cognitive engagement. In rehabilitation, for example, robotic devices can guide limb movements with high accuracy, ensuring safe joint trajectories and resistance levels, while VR environments deliver motivating and contextualized tasks that simulate real-life scenarios, promoting motor learning and functional recovery [131], [132], [133]. Immersive VR feedback also boosts patient motivation and adherence, which are critical for long-term therapy success [134]. The integration of robotics and VR further enables precise data collection: robotic sensors capture movement kinematics, force output, and muscle activation patterns, while VR tracks gaze, attention, kinematics, and interaction behaviors. Overall, this synergy offers a unique blend of precision, engagement, and personalization, making interventions not only more effective but also more enjoyable and accessible [135]. As technology advances, VR-robotics integration promises to redefine standards in therapy, assessment, and training across multiple healthcare domains.

2.2.2 Industrial applications

Smart technologies are also transforming the industrial domain, introducing new tools and systems that support productivity, safety, and worker well-being. In particular, the industrial domain is undergoing a transformative shift with the emergence of collaborative robots (cobots), which are reshaping the human–machine interface and redefining the nature of human–robot interaction.

Human–Robot Interaction encompasses different modes of engagement, classified according to workspace sharing, task goals, and temporal dynamics [136]. Human–Robot Coexistence occurs when both agents operate in the same workspace on independent tasks. Human–Robot Cooperation describes scenarios in which humans and robots share an objective but do not depend on each other to complete it [137]. Human–Robot Collaboration (HRC) represents the most integrated form of interaction, where humans and robots simultaneously work on the same task, within the same workspace, continuously adapting to each other's actions [138], [139]. Historically, industrial robots were large, high-speed machines designed to operate in physical isolation from human workers due to safety concerns. Their role was primarily confined to repetitive, hazardous, or high-precision operations, while humans managed tasks requiring adaptability, judgment, or fine motor control. On the other hand, recent advances in sensing, control, and safety standards have opened the way for a new generation of robots that collaborate with humans, giving rise to HRC, which has become a key area of focus in robotics research [140], [141], [142].

Cobots are equipped with features such as force and torque sensing, vision-based perception, and advanced control algorithms that allow them not only to safely share workspaces with humans but also to actively cooperate in task execution (e.g., passing objects, assisting in assembly, or performing ergonomically demanding movements). Unlike traditional robots that operate in isolation, cobots are designed to share the same workspace, resources, and – in some cases – the same tasks with humans [143]. In HRC, humans and robots work side by side toward shared goals, engaging in continuous interactions where they adapt and respond to each other's actions [139]. This synergy enhances efficiency and productivity, since human abilities complement robotic precision, strength and endurance [144]. The aim of HRC is to combine the strengths of both partners: the strength, endurance, and precision of robots with the intuition, flexibility, and problem-solving abilities of humans [143]. This integration holds great promise, reducing musculoskeletal strain, minimizing fatigue, and increasing overall productivity.

However, the transition toward HRC introduces new challenges. Effective collaboration extends beyond technical safety and requires understanding how humans perceive, adapt to, and perform in shared environments. Key questions concern how HRC influences postural control, motor coordination, attention, cognitive workload, and trust. From an ergonomic perspective, cobots can reduce physical workload by assisting with heavy, repetitive, or awkward tasks, thereby lowering musculoskeletal strain and improving postural ergonomics [141], [145]. However, sharing control and space with a robot may introduce new postural adjustments or compensatory movements, especially when synchronization or timing is suboptimal. On the cognitive level, HRC can redistribute mental effort: while automation relieves workers of routine operations, it often increases monitoring demands and attentional load, requiring continuous prediction and supervision of robot actions [146]. Psychosocially, cobots can enhance engagement and motivation by fostering a sense of innovation and teamwork, yet they may also elicit stress or mistrust if transparency and predictability are lacking [147]. Motor coordination and sensorimotor adaptation must also be considered, as humans need to align their movement dynamics with the robot's motion patterns, potentially improving joint-action fluency but sometimes disrupting natural motor control [148]. However, the motor aspects of HRC remain insufficiently investigated, since most studies tend to assume that collaboration with robots simply reduces physical demands on workers.

To address these challenges, traditional methods for assessing human factors in HRC heavily rely on subjective questionnaires, even though objective methods are gaining popularity [149]. Although questionnaires are versatile, time-efficient, low-cost, straightforward to use and easy to analyze [150], they present several drawbacks, principally due to their inherent subjectivity, which might potentially lead to inaccuracies or incomplete representations of well-being. Indeed, outcomes may be influenced by individual biases, perceptions, moods, and other subject-related factors [151], [152]. Certain limitations could be overcome by opting for objective methods, since they are less susceptible to voluntary influence and provide explicit continuous measurement [153]. They provide precise, reliable, and replicable data, reduce human error through automation, minimize intrusiveness via wearable sensors, and enable real-time monitoring, supporting dynamic analysis and improved human–robot task allocation [146], [154], [155], [156], [157]. Therefore, considering the limitations of subjective methods and the advancements in technologies, objective approaches are expected to complement subjective ones, enabling efficient data collection and providing richer and more comprehensive insights [153], [158].

3

Analysis of sensorimotor impairments in Alzheimer's Disease continuum in Virtual Reality environments

This chapter presents the first study, which investigates sensorimotor impairments in patients with Alzheimer's Disease (AD), individuals with Mild Cognitive Impairment (MCI), and age-matched healthy controls (HC) when performing reaching and catching tasks in immersive VR environments. Within the framework of the central hypothesis of this thesis, immersive VR is conceptualized as a structured experimental perturbation of the sensorimotor system, eliciting adaptive changes in motor behavior that can be quantitatively characterized. Specifically, this study tests whether cognitively impaired individuals exhibit a progressive reduction in kinematic performance, together with systematic alterations in anticipatory and execution-related movement features, compared to age-matched healthy controls. The identification of quantitative kinematic markers is aimed at supporting early diagnosis and monitoring of neurodegenerative progression through the analysis of upper-limb motor behavior.

Section 3.1 introduces the motivation and clinical relevance of the study. It emphasizes the importance of developing sensitive tools for early diagnosis, focusing on the role of motor assessments as complementary indicators to cognitive evaluations. It also highlights how immersive VR can provide an ecologically valid and controlled framework for investigating sensorimotor performance in cognitively impaired individuals.

Section 3.2 describes in detail the materials and methods adopted in this study: participants characteristics (3.2.1), experimental setup (3.2.2), experimental protocol (3.2.3), data analysis (3.2.4), and statistical analysis (3.2.5).

Section 3.3 presents the study findings, organized into three parts: reaching task results (3.3.1), catching task results (3.3.2), and Linear Discriminant Analysis outcomes (3.3.3).

Section 3.4 provides an in-depth discussion of the findings. It interprets the observed differences in terms of motor control, cognitive processing, and learning mechanisms, also highlighting how altered motor planning and reduced flexibility characterize the transition from MCI to AD. Here, also the importance of task naturalism is deeply discussed, demonstrating that external sensory cues can partially compensate for impaired motor planning in AD.

Section 3.5 presents the conclusions of the study, emphasizing the novelty and potential of VR environments for assessing sensorimotor and cognitive impairments in neurodegenerative conditions.

3.1 Motivation and clinical relevance

The aging of the global population represents one of the most significant demographic and social changes of the 21st century [159], [160]. Rapid advances in medical science, public health, and socioeconomic development have collectively contributed to an unprecedented increase in human longevity [159], [161], [162]. As a result, the number of individuals aged 60 and over is growing rapidly: by 2050, it is estimated that there will be more than 2.1 billion people aged 60 and over, representing over 21% of the global population [163].

As societies age, the implications for healthcare systems become increasingly complex [159]. Longer life expectancy is frequently accompanied by an increase in chronic diseases such as cardiovascular diseases, cancer, diabetes, and neurodegenerative conditions such as Alzheimer's disease [164]. These non-communicable diseases now represent the majority of deaths worldwide and disproportionately affect older populations [165]. Neurological diseases are the second leading cause of death and the first cause of severe long-term disability in the world, thus requiring a multidisciplinary approach to find solutions to tackle this burden in older adults [166]. In particular, the prevalence of Alzheimer's Disease – which is the most common cause of dementia – increases substantially with age [166].

The Alzheimer's Disease involves progressive cognitive and motor decline, often leading to significant impairment in daily activities and typically being diagnosed only after irreversible damage has occurred [162]. Thus, there is a critical need for sensitive and reliable methods for early diagnosis and monitoring of disease progression [167]. Moreover, many individuals experience Mild Cognitive Impairment, which is a transitional state that often precedes dementia, offering a critical window for early intervention. Traditionally, diagnostic approaches have centered on cognitive assessments, evaluating domains such as memory, language, and executive function [168]. However, performance in cognitive tests may be influenced by several non-disease-related factors, including educational background, language proficiency, and examiner-dependent scoring, which can limit their sensitivity and comparability across individuals. Emerging evidence highlights the value of motor assessments, since sensorimotor impairments can precede detectable cognitive decline [169], [170], [171]. In this context, motor-based evaluations offer complementary advantages, as they rely on objective and quantitative performance measures that can be more easily standardized and may capture subtle functional alterations that emerge in the early stages of neurodegenerative disorders. Individuals with AD and MCI often exhibit impairments in fine motor control and coordination, affecting tasks such as handwriting [172], [173], [174], finger tapping [175], and gait [176], [177]. Other motor signs, such as rigidity, reduced lower extremity function, and variability in repetitive movements, are linked to higher risk of cognitive decline, institutionalization, and mortality [178], [179], [180], [181]. Importantly, motor tasks can distinguish healthy controls from MCI and AD participants with sensitivity comparable to cognitive tests [182], [183]. Thus, the identification of sensorimotor biomarkers (i.e., quantitative indicators that reliably distinguish cognitive-impaired individuals from healthy controls) holds promise for early diagnosis and longitudinal monitoring.

Specifically, reaching and catching upper-limb movements are particularly informative, as cognitive decline is associated with generalized slowing of movement, reflecting deficits in visuomotor planning [184]. These goal-directed upper-limb actions require the integration of visual perception, motor planning, and online movement correction, processes that are known to be affected in the early stages of neurodegenerative disorders. For example, AD patients perform slower and less accurate reaching movements, especially in the absence of visual feedback [185], [186], [187], highlighting impairments in integrating sensory information with motor planning. Moreover, tasks involving interception require anticipatory control and precise timing, making them particularly sensitive to subtle impairments in visuomotor coordination that may emerge before overt functional limitations become evident. Evaluating fine motor features across stages of reaching and catching could provide critical insights for both diagnosis and targeted interventions.

In this context, immersive Virtual Reality (VR) represents a valuable alternative to traditional laboratory-based motor assessments. Compared to conventional tasks, VR environments allow researchers to precisely control task parameters while maintaining high experimental reproducibility. At the same time, the immersive nature of VR can increase ecological validity and participant engagement by simulating interactive scenarios that resemble real-world actions. Moreover, VR systems can be integrated with motion-tracking technologies to capture detailed kinematic data, providing more comprehensive quantitative information than many conventional clinical assessments. By combining precise kinematic tracking with controlled yet ecologically valid environments, immersive VR enables the simulation of realistic tasks while capturing detailed motor behavior. Consistent with this potential, VR-based interventions have demonstrated improvements in navigation and cognitive-motor function in individuals with MCI and AD, supporting its utility as both an evaluative and therapeutic tool [188], [189], [190], [191].

Building on this evidence, the present study aims to examine planning and execution of reaching and catching movements in AD, MCI, and age-matched HC using immersive virtual reality. Of particular interest are anticipatory aspects of movement, such as the ability to wait for a go signal before initiating action, as these mechanisms may reveal subtle deficits in inhibitory control and motor planning that emerge early in neurodegeneration. Kinematic parameters extracted from VR are used to characterize group-level differences in adaptive motor behavior, which are expected to follow a graded pattern (HC > MCI > AD). These differences are further expected to be modulated by task context, with more externally cued conditions reducing group separability. In addition, cognitively impaired participants are expected to exhibit increased anticipatory responses. By integrating quantitative motor assessment with immersive VR technology, this study aims to contribute to the development of scalable, ecologically valid tools for early detection, monitoring, and intervention across the spectrum from healthy aging to Alzheimer's disease.

3.2 Materials and methods

3.2.1 Participants

A total of 61 individuals (31 females, 30 males; age = 72 ± 6 years) participated in the experimental campaign after providing written informed consent. The research protocol was approved by the Ethical Review Board of Fondazione Santa Lucia (Protocol CE/PROG.820) and conducted in accordance with the principles outlined in the Declaration of Helsinki.

Participants were divided into three groups based on their cognitive status: 19 individuals diagnosed with Alzheimer's disease (AD), 21 with Mild Cognitive Impairment (MCI), and 21 healthy age-matched controls (HC). AD and MCI participants were recruited from the Memory Clinic of Fondazione Santa Lucia and diagnosed according to internationally recognized clinical criteria [192], [193]. Inclusion in the AD group required a Mini-Mental State Examination (MMSE) score between 14 and 26 at screening [194], [195]. MCI participants represented the early symptomatic stage of Alzheimer's disease, characterized primarily by episodic memory impairment in the absence of general cognitive or functional decline. All patients had no prior history of cognitive or memory deficits before symptom onset.

Stringent exclusion criteria were applied to ensure the homogeneity and validity of the sample: participants with major systemic illnesses, psychiatric disorders, or other neurological conditions were excluded. To control potential confounds related to motor experience, all participants were right-handed (as assessed by the Edinburgh Handedness Inventory), and none of them had professional experience in sports requiring ball-catching skills. This careful selection allowed for a balanced comparison between groups while minimizing variability due to confounding factors. Figure 1 summarizes the demographic characteristics and MMSE scores for each group, providing a clear overview of participant distribution, age, and cognitive performance at baseline.

group / measure	HC	MCI	AD
total number (male)	21 (7)	21 (13)	19 (10)
age (std)	68.8 (6.5)	74.0 (6.5)	73.9 (5.8)
MMSE score (std)	29.3 (1.0)	25.5 (3.0)	21.4 (2.7)

Figure 1. Characteristics of the three groups of participants enrolled in the study.

3.2.2 Experimental setup

Upper-limb reaching and catching tasks were conducted in an immersive VR environment developed to present visual stimuli with controlled timing and trajectories, track hand and head movements in real time using integrated sensors, and minimize extraneous cognitive demands to focus on core visuomotor performance. Upper-limb movements were recorded using the HTC Vive Pro 2 VR system (HTC, Taoyuan, Taiwan), which consisted of a headset, a handheld controller, a tracker, and two base stations for spatial calibration. The headset provided a stereoscopic display at a 90 Hz refresh rate with a 120° field of view and included integrated earphones for audio feedback. Participants held the controller in their right hand, while the tracker was securely attached to the right wrist using a Velcro strap, enabling independent monitoring of hand position. Kinematic data were collected via embedded MPU-6500 Six-Axis MEMS motion-tracking sensors combining gyroscope and accelerometer functions, located in the headset, controller, and tracker. These inertial sensors, together with spatial tracking from the base stations, provided high-resolution recordings of hand and head movements in three-dimensional space throughout task performance.

The virtual environment was implemented using custom-made C# scripts in Unity (Unity Technologies, San Francisco, CA), a real-time 3D development platform and game engine. These scripts have been written to control task logic, target presentation, and timing of events, as well as to log kinematic data in real time. The software tool SteamVR (Valve Corporation, Bellevue, WA) was used to interface Unity with the HTC Vive hardware devices, ensuring precise synchronization between task events and motion capture. This configuration allowed the collection of detailed, temporally aligned kinematic data while maintaining an ecologically valid and engaging virtual environment for participants.

3.2.3 Experimental protocol

Participants received verbal instructions on how to perform the experimental tasks. To enhance comprehension, video demonstrations were also provided, showing a laboratory staff member executing the tasks. Prior to the start of the experiment, participants were introduced to the virtual environment to ensure familiarity and ease of interaction. All participants remained seated throughout the session to eliminate any risk of instability or falls that could arise due to potential discomfort associated with VR immersion.

The virtual environment was designed to replicate the physical room in which the experiment was conducted, reducing spatial disorientation and facilitating a seamless transition between real and virtual spaces. Participants were seated on a chair positioned at a predefined location within the experimental room, which corresponded precisely to their virtual position. This alignment ensured spatial consistency across real and virtual frames of reference. Figure 2 illustrates the experimental setup, including the positioning of an exemplary participant.

Figure 2. Illustration of an individual equipped with all the sensors employed in the study, posed to initiate the task within the experimental setup. The person is wearing the headset, is holding the controller with their right hand, and has the tracker attached to their right wrist.

Tasks were organized into multiple blocks. Short breaks were provided between each block to prevent fatigue and allow participants to rest. During these breaks, participants were asked about their physical well-being, specifically whether they experienced any symptoms commonly associated with VR exposure, such as dizziness, nausea, or general discomfort. If any symptoms were reported, the duration of the break was extended to allow for adequate recovery. In cases where discomfort persisted, the experiment would have been terminated to prioritize the participant's safety. This check-in protocol was also repeated at the end of the session to ensure continued well-being. Notably, none of the participants included in the study reported any adverse symptoms. All individuals remained engaged throughout the experimental procedure and described the VR experience as enjoyable.

Reaching task

At the beginning of the reaching task, participants viewed a virtual cursor – a yellow sphere with a diameter of 5 cm – linked to the position of the handheld controller. They were first instructed to move this cursor to a designated home position, which was visually represented as a larger blue sphere (9 cm in diameter) located at the center of a grey circular board positioned directly in front of them. After maintaining the cursor at the home position, a random time interval between 1 and 1.5 seconds elapsed, after which the central blue sphere disappeared. Simultaneously, a new blue target sphere appeared at one of eight possible peripheral positions, equally spaced along the circumference of the board at a radial distance of 30 cm from the center. To facilitate task understanding and minimize cognitive load, target positions were not presented in random order but in a fixed counterclockwise direction, beginning with the topmost location.

Upon disappearance of the central home sphere and appearance of the target, participants were required to move the yellow cursor from the home position to the target position within 750 milliseconds of movement onset. Movement onset was determined online, defined as the moment when the controller's speed exceeded 5 cm/s or when the controller had moved more than 5 cm from the home position. Initially, a more stringent time threshold of 500 ms was tested during pilot sessions; however, this proved overly restrictive, as most participants were unable to consistently meet the requirement. Thus, to better accommodate participant performance across groups, the allowable response window was extended to 750 ms. If the target was not reached within the specified time frame, the target sphere disappeared, and the trial was recorded as unsuccessful. Conversely, if the cursor reached the target within the designated time, participants were instructed to maintain the yellow sphere within the blue target sphere for one second, until the target disappeared. Following this, they were required to return the cursor to the home position to begin the next trial.

Figure 3 shows two snapshots from the participant's perspective within the VR environment. The left panel depicts the moment when the yellow cursor is correctly positioned inside the blue home sphere, while the right panel captures the scene at the movement onset, right after the go signal, marked by the appearance of the target blue sphere.

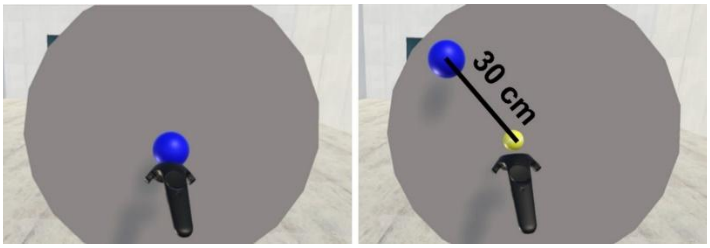

Figure 3. VR view of participants in two distinct temporal snapshots: immediately following the start time on the left and at the movement onset time on the right. The Euclidean distance between the target position and the home position was always equal to 30 cm, regardless of the position of the target ball on the circular board.

The reaching task consisted of 10 blocks, following an initial familiarization block. Each block contained one trial per target location, resulting in a total of 80 experimental trials. This block-based design allowed for short rest periods between blocks, helping maintain participant engagement and reduce fatigue across the session.

Catching task

At the beginning of the catching task, participants viewed a white virtual racket visually attached to the back of the handheld controller. The task required participants to intercept a virtual ball – launched from six meters ahead – using this racket. Successful interception was confirmed through both visual and auditory feedback: when the participant caught the ball, it remained visibly attached to the racket, and a brief acoustic signal was simultaneously delivered through the earphones integrated in the VR headset. This multimodal feedback allowed participants to clearly perceive task success.

Before each trial began, participants were required to place the controller in a self-selected home position. The trial would only begin once the controller was correctly positioned at this location, ensuring consistency in starting posture across repetitions. As illustrated in Figure 4, the catching task was performed under three distinct experimental conditions, which were randomly assigned across trials.

Figure 4. VR view of participants in three distinct experimental conditions. The black lines, which represent the ball trajectories, were not visible to the participants but are included here to clarify the paths in each condition.

In the first condition, the virtual environment included a visible virtual thrower. This thrower corresponded to a real human individual, whose movements were recorded in the laboratory using a motion tracking system and subsequently rendered in the VR environment. This person had taken part in previous studies [196], [197], and their kinematic data were used to reproduce the natural throwing action. Accordingly, the ball trajectory was also derived from the real motion capture data, thus ensuring a realistic path influenced by gravity.

In the second condition, the virtual thrower was absent, but the ball's motion continued to follow a gravity-influenced parabolic path. This condition was implemented to investigate whether the absence of a visible thrower affected performance. Previous research demonstrated that observing the thrower's full movement, in addition to the ball's flight, can enhance prediction and improve task performance [198], consistent with the broader role of anticipatory processes in everyday motor behavior [199].

In the third condition, both the virtual thrower and gravitational effects were removed from the VR environment. Consequently, the ball followed a non-parabolic trajectory uninfluenced by gravity. The without-gravity trajectory was matched in terms of endpoint location to the corresponding with-gravity trajectory, ensuring that interception occurred at the same spatial location across conditions. This manipulation was designed to assess the role of gravitational cues in motor prediction and interception, and to explore whether the reliance on internal models of gravity differed across the three subject groups. Prior studies suggested that, even when presented with altered motion trajectories, individuals continue to rely on internal representations of gravitational acceleration to guide their interception behavior [200].

Each of the three experimental conditions included four distinct target positions: bottom left, bottom right, top left, and top right, relative to the participant's field of view. These target locations were derived from the studies that provided the thrower kinematics and ball trajectory data [196], [197]. With 5 repetitions per target position and condition, the total number of trials amounted to 60. These trials were distributed across five blocks of 12 trials each. Short rest periods were provided between blocks to prevent fatigue. Participants were encouraged to rest as needed, and the next block began only after they confirmed they were ready to proceed.

3.2.4 Data analysis

Kinematic data recorded from the controller were analyzed to evaluate participants' motor performance across both tasks. Data processing was conducted using custom scripts developed in MATLAB (MathWorks, Natick, MA). The position and orientation of the controller, originally sampled at 90 Hz by the HTC Vive system, were resampled at 100 Hz to standardize the temporal resolution. To reduce high-frequency noise, kinematic signals were low-pass filtered using a zero-lag fourth-order Butterworth filter with a 10 Hz cut-off frequency. From the filtered data, several temporal, kinematic and performance parameters of interest were extracted for each trial in both the reaching and catching tasks to characterize participant behavior during the tasks.

Reaching task parameters

Reaching temporal parameters were defined as follows: *start time*, corresponding to the beginning of the trial; *go time*, corresponding to the stimulus presentation (i.e., the disappearance of the central sphere and simultaneous appearance of the target sphere); *impact time*, considered only in successful trials and defined as the moment when the cursor sphere touched the target sphere; *end time*, corresponding to the completion of the trial. Reaching kinematic parameters included the followings: *onset time*, defined as the moment when the controller's speed reached 10% of its maximum value; *reaction time*, calculated as the interval between the go signal and movement onset; *maximum speed*, defined as the peak value of the controller's speed during the trial; *peaks number*, calculated as the count of local speed peaks identified by negative zero-crossings in acceleration throughout the movement. Reaching performance was evaluated through *success rate*, defined as the proportion of successful trials (i.e., when the controller intercepted the target), and *spatial error*, calculated as the smallest Euclidean distance between the controller and the target position.

Additionally, anticipatory behavior was assessed using specific anticipation metrics. Since participants were instructed to move the cursor only after the go signal, anticipatory responses were identified as peaks in the speed profile occurring before the go signal. Thus, the *anticipation rate* was then defined as the fraction of trials in which anticipatory responses occurred. To further characterize these responses, two displacement vectors were calculated: (1) from the center of the home sphere to the cursor's position at the time of maximum distance from the home sphere during the anticipation interval, and (2) from the center of the home sphere to the center of the target sphere. The angle between the projections of these vectors onto the frontal plane was defined as the *anticipation direction*, describing the aiming direction during anticipatory responses. Figure 5 illustrates the two vectors used to compute the anticipation direction angle.

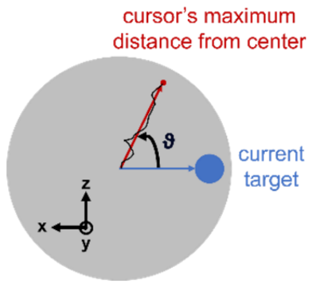

Figure 5. Computation of the anticipatory direction. The red arrow represents the displacement of the cursor at its maximum distance from the home position during the anticipatory response. The blue arrow represents the direction of the target of the current trial. The angle θ between these two vectors indicates the direction of the anticipatory movement (i.e., the "anticipation direction").

Catching task parameters

Catching temporal parameters were defined as follows: *start time*, corresponding to the beginning of the trial; *go time*, corresponding to the stimulus presentation (i.e., the launch of the virtual ball toward the participant); *impact time*, considered only in successful trials and defined as the moment when the racket intercepted the ball; *end time*, corresponding to the completion of the trial. Catching kinematic parameters included the following: *onset time*, defined as the moment when the controller's speed reached 10% of its maximum value; *reaction time*, calculated as the interval between the go signal and movement onset; maximum speed, defined as the peak value of the controller's speed during the trial; *peaks number*, calculated as the count of local speed peaks identified by negative zero-crossings in acceleration throughout the movement.

Catching performance was evaluated through different parameters. *Success rate* was defined as the proportion of successful trials (i.e., when the racket intercepted the ball). *Spatial error* was computed by first calculating the Euclidean distance between the controller and ball positions at each sample and then taking the minimum value of these distances. *Minimum distance* was calculated by selecting ball positions within a specific spatial region (i.e., within 1 m of the controller's starting position), computing for each controller sample the Euclidean distance to all selected ball positions, and taking the minimum of these distances, which could correspond to different samples of the controller and the ball.

Linear Discriminant Analysis

The complete set of features served as input variables for Linear Discriminant Analysis (LDA) aimed at discriminating between subject groups, by using the caret package in R (v 2023.03.1+446, R Core Team, Vienna, Austria). All features were centered and scaled prior to model fitting. Model performance was assessed using Leave-One-Subject-Out (LOSO) cross-validation, such that each observation was predicted by a model trained on all other subjects, thereby avoiding evaluation on the training set. Cross-validated predictions were used to compute overall classification accuracy as well as class-specific accuracy (i.e., sensitivity for each diagnostic group). A confusion matrix was constructed to summarize prediction outcomes, and class-specific sensitivity, specificity, and balanced accuracy were extracted.

3.2.5 Statistical analysis

Statistical analysis of the metrics was performed using Generalized Linear Mixed Models (GLMMs) in R (R Core Team, Vienna, Austria). GLMMs incorporate both fixed and random effects, making them particularly useful for analyzing binomial responses considering participants' differences when analyzing single trials.

The statistical analysis was implemented to differentiate the three groups of participants on several metrics of interest: *success rate*, *reaction time* and *maximum speed* in both reaching and catching and *anticipation rate* in reaching tasks. The general forms used to test the difference between the subject group are given by equation (1) for the reaching task and equation (2) for the catching task.

$$Y_{ij} = \beta_{0i} + \beta_{group} Group_{ij} + \beta_{target} Target_{ij} + \beta_{block} Block_{ij} + S_i + \varepsilon_{ij} \quad (1)$$

$$Y_{ij} = \beta_{0i} + \beta_{group} Group_{ij} + \beta_{target} Target_{ij} + \beta_{block} Block_{ij} + \beta_{Cond} Cond_{ij} + S_i + \varepsilon_{ij} \quad (2)$$

For each subject i and each trial j, Y_{ij} is the response variable, β are the fixed-effects coefficients, S_i are the random-factors coefficients, and ε_{ij} are the residual error terms. *Group* is a categorical variable with three levels (AD, MCI and HC). *Target* is a categorical variable with 8 levels for the reaching task and 4 levels for the catching task. *Block* is a continuous variable with 10 levels for the reaching task and 5 levels for the catching task, one for each block. *Cond* is a continuous variable with 3 levels, one for each catching experimental condition.

Pairwise comparisons between all groups were obtained by running two GLMMs with different reference levels for the group factor. P-values were subsequently adjusted using Bonferroni correction to control for multiple testing.

Additionally, for reaching tasks, statistical analysis has also been conducted for anticipatory metrics. To assess the effect of the presence of anticipatory behavior on performance, the model has also been tested in equation (3).

$$Success_{ij} = \beta_{0i} + \beta_{anticipation} Anticipation_{ij} + \beta_{group} Group_{ij} + S_i + \varepsilon_{ij} \quad (3)$$

where $Success_{ij}$ is the binary variable indicating a successful reaching movement of subject *i* in trial *j*, and *Ant* is the presence of anticipation in that trial. Another GLMM has been tested to investigate the dependency of the anticipation rate from the MMSE score and the group, as reported in equation (4).

$$Anticipation_{ij} = \beta_{0i} + \beta_{MMSE}MMSE_{ij} + \beta_{group}Group_{ij} + S_i + \varepsilon_{ij} \quad (4)$$

Finally, statistical analysis on the *anticipation direction* has been conducted through the Rayleigh Test of Uniformity, accounting for circular data characteristics [201].

The significance level was set to 0.05, 0.01 and 0.001 (*, ** and ***, respectively).

3.3 Results

3.3.1 Reaching task parameters

Qualitative differences between the three groups were investigated by visually comparing the paths and speed profiles of the controller. Figure 6 represents the paths and speed profiles of three exemplary subjects, one for each group. Speed profiles for each trial are aligned to the *go time*, thus the time interval before the vertical dashed line includes anticipatory responses. The HC subject displays the smoothest movement pattern, while movement smoothness appears progressively reduced in the MCI and AD subjects. Furthermore, the AD participants show the highest number of anticipatory responses, whereas almost no anticipatory behavior is present in the HC participant.

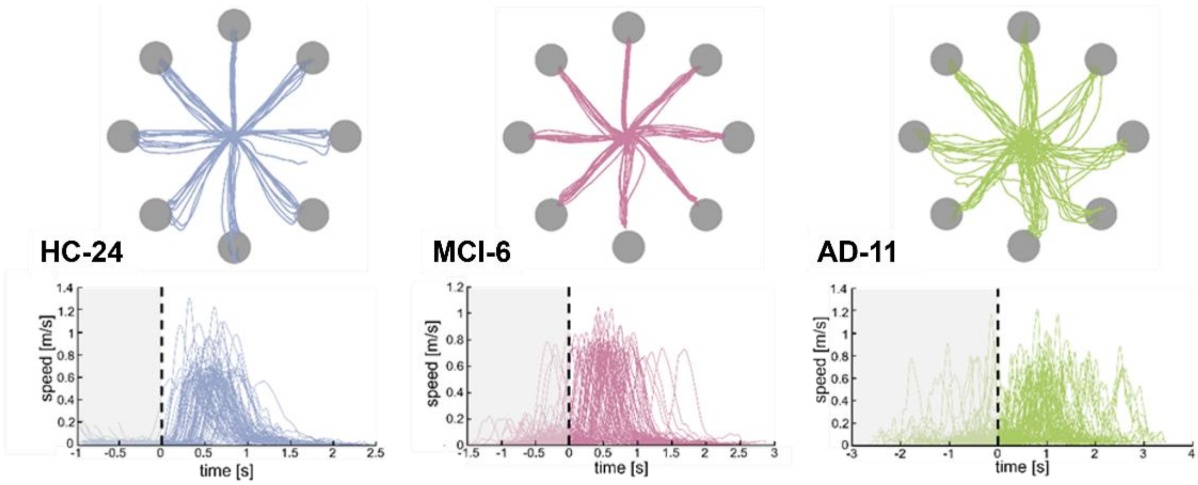

Figure 6. Controller's paths and speed profiles of the whole trial of 3 exemplary participants, one for each group. Each line represents one trial. The 8 grey circles represent the 8 target positions. Times in the abscissa of the speed profiles plots are referred to the go time, thus the area before the vertical dashed line comprehends anticipatory responses.

To investigate whether these qualitative observations reflected broader group-level trends in motor performance, quantitative metrics were analyzed: success rate, reaction time, maximum speed and anticipation rate.

Results from the analysis of success rate are reported in Figure 7. AD participants exhibited the lowest success rate, with a statistically significant difference compared to the HC group ($p < 0.01$; $\beta = -2.31$). MCI participants showed intermediate performance, suggesting a gradual decline from healthy aging to more severe cognitive impairment, although not significantly different from either HC or AD participants.

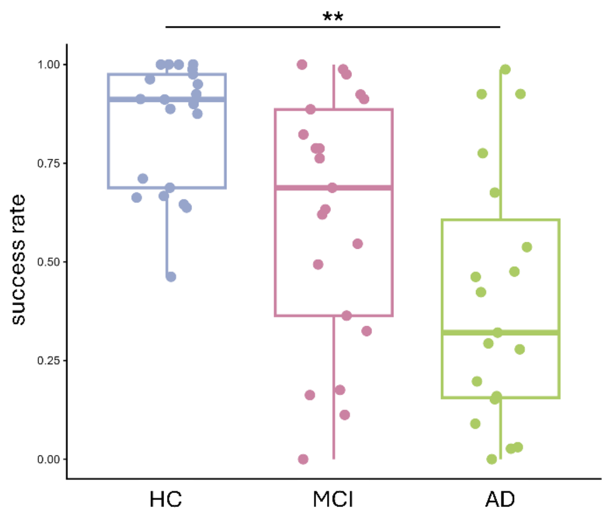

Figure 7. Success rate of the three different groups of participants. For each group, the boxplot indicates the distribution of success rates, while each point represents a single subject.

Performance improved with repetitions: success rate increased with blocks ($\beta_{block} = 0.18$; $p < 0.001$), but this was true only for the healthy group as shown by the significant interaction between Block and Group (MCI × block: $\beta = -0.15$; $p < 0.001$; AD × block: $\beta = -0.18$; $p < 0.001$). Figure 8 shows the GLMM prediction for each individual in each group.

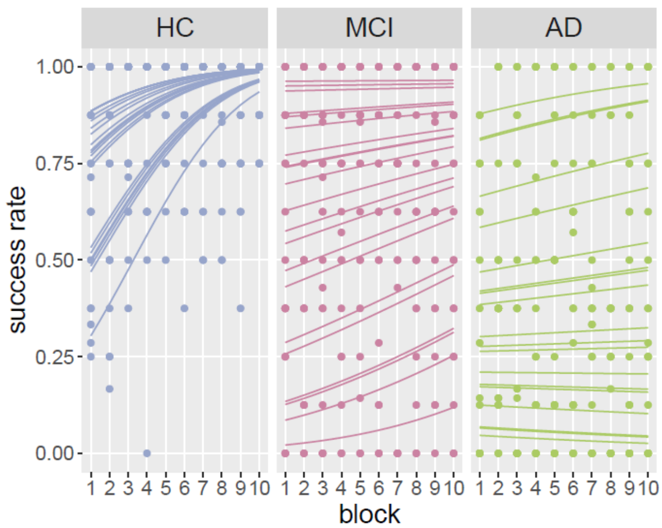

Figure 8. Success rate for each participant in each block. Continuous lines indicate the prediction of the GLMM.

As reported in Figure 9, reaction time analysis revealed that HC participants responded significantly faster than both MCI ($p < 0.01$; $\beta = 0.29$) and AD ($p < 0.05$; $\beta = 0.2$).

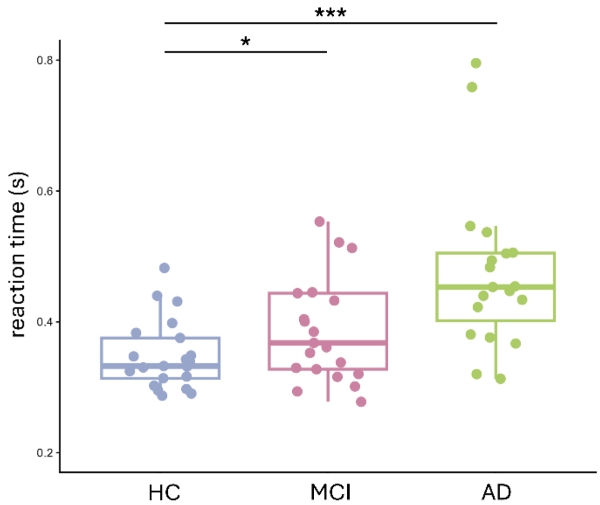

Figure 9. Reaction time of the three different groups of participants. For each group, the boxplot indicates the distribution of reaction times, while each point represents a single subject.

Further insight was gained by examining the maximum speed of the controller movements for each group (Figure 10). Results reveal that HC participants achieve higher maximum speeds than both MCI and AD groups, with statistically significant differences observed between HC and MCI ($p < 0.001$; $\beta = -0.2$) and between HC and AD ($p < 0.001$; $\beta = -0.29$).

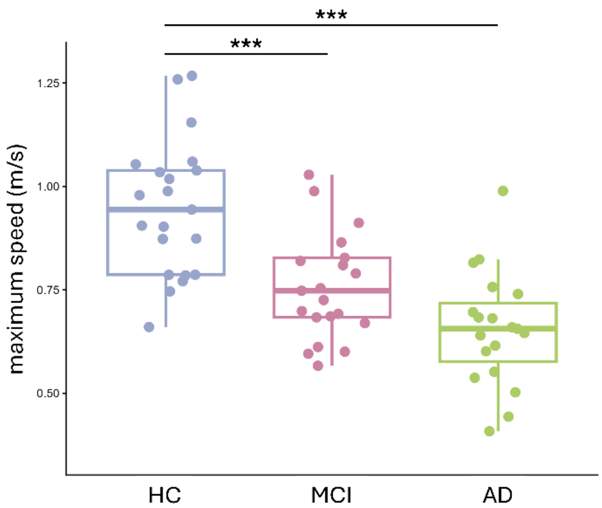

Figure 10. Maximum speed of the controller for the three different groups of participants. For each group, the boxplot indicates the distribution of maximum speeds, while each point represents a single subject.

Finally, to assess whether a heightened propensity for anticipatory responses was a general characteristic of AD individuals, anticipation rates were examined in all three groups (Figure 11). Consistent with our expectations, the lowest level of anticipatory behavior was observed in HC subjects, with a statistically significant difference compared both to the MCI group ($p < 0.05$; $\beta = 1.06$) and AD group ($p < 0.001$; $\beta = 1.86$). No significant difference between the MCI and AD groups was found.

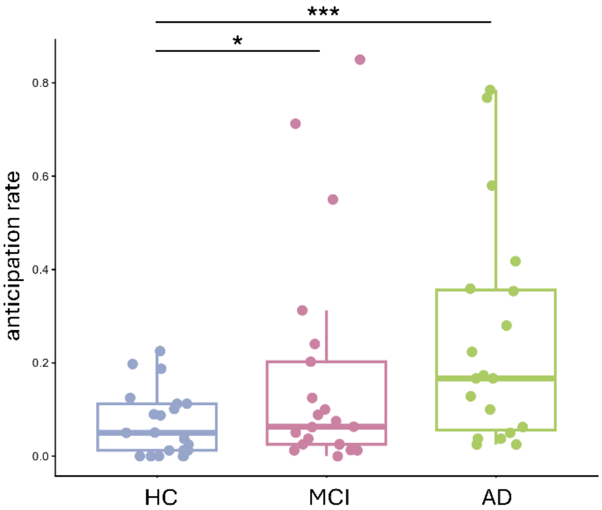

Figure 11. Anticipation rate of the three different groups of participants. For each group, the boxplot indicates the distribution of anticipation rates, while each point represents a single subject.

In addition, anticipation behavior is more likely to occur during the early blocks (as indicated by the negative slope of the block coefficient in the GLMM: $\beta = -0.05$; $p < 0.01$), and when reaching towards the first targets (as indicated by the negative slope of the target coefficient in the GLMM: $\beta = -0.09$; $p < 0.001$).

Considering the preceding findings about the correlation of success rate and anticipation rate, the likelihood of trial success given the presence or absence of anticipatory responses was also evaluated. To this aim, a GLMM was tested to investigate the dependency of the success rate from the anticipation rate and the group. Results indicate that there is a significant effect of anticipation, i.e., participants were more likely to reach the target if they did not move before the go signal ($\beta = -1.19$; $p < 0.001$). Accordingly, Figure 12 displays the coefficients of the GLMM for the group and the absence/presence of anticipatory responses. This figure highlights the inverse relationship between the probability of trial success and anticipatory behavior: individuals with enhanced levels of anticipation are less likely to achieve trial success. These findings emphasize how anticipatory behavior negatively affects task performance, with varying impacts observed across different participant groups.

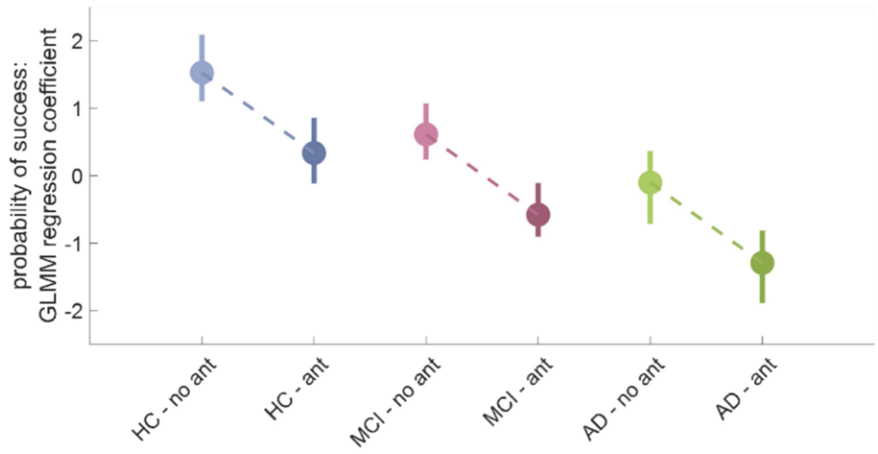

Figure 12. GLMM coefficients for the probability of successful trials as a function of participant group and anticipation behavior. Colors denote groups, with lighter/darker shades indicating absence/presence of anticipatory responses. Markers represent mean coefficients, and error bars show the range (min-max).

Furthermore, Figure 13 shows the correlation between the anticipation rate and the MMSE score. Consistent with expectations, elevated MMSE scores, indicative of less impairment, exhibit a corresponding decrease in anticipation rate ($\beta = -0.15$, $p < 0.01$). This observation underscores the broader relationship between cognitive function, as assessed by the MMSE, and anticipatory behavior.

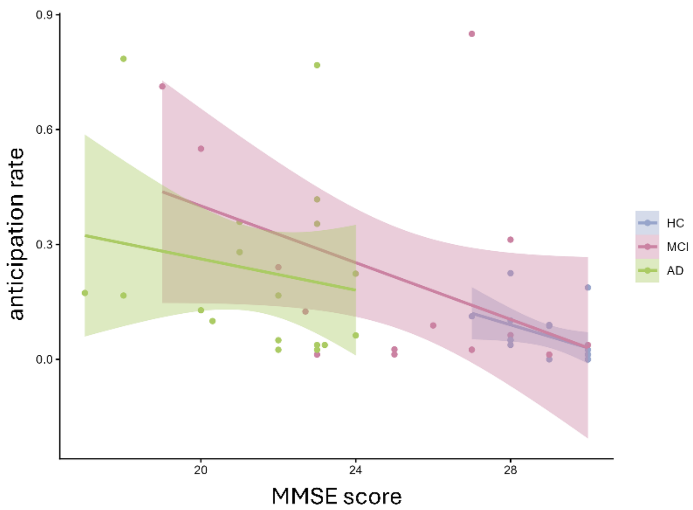

Figure 13. Correlation between anticipation rate and MMSE score for each of the three groups of subjects. Groups are denoted by colors: blue for HC, pink for MCI, and green for AD. Each point indicates one single subject.

Finally, the direction of the anticipatory movements provided additional insights. In Figure 14, polar histograms visually portray the distribution of direction angles of anticipatory movements on the frontal plane across all trials and subjects for each group. In the polar histograms, targets of the current, preceding, and subsequent trials are oriented at 0°, 345°, and 45°, respectively. We tested whether the angle distribution for each population was different from a random uniform distribution (Rayleigh Test of Uniformity). The distribution for HC participants, who exhibited the fewest anticipatory movements, was not significantly different from a uniform distribution (p = 0.73). Similarly, the distribution of MCI subjects, who showed an increase in anticipatory movements, did not differ from a uniform distribution (p = 0.10). In contrast, a more peaked distribution could be appreciated for the AD group, indicating that during an anticipatory behavior AD participants aimed mostly towards the previous target ($\mu = 308° \pm 3°$, $p < 0.05$).

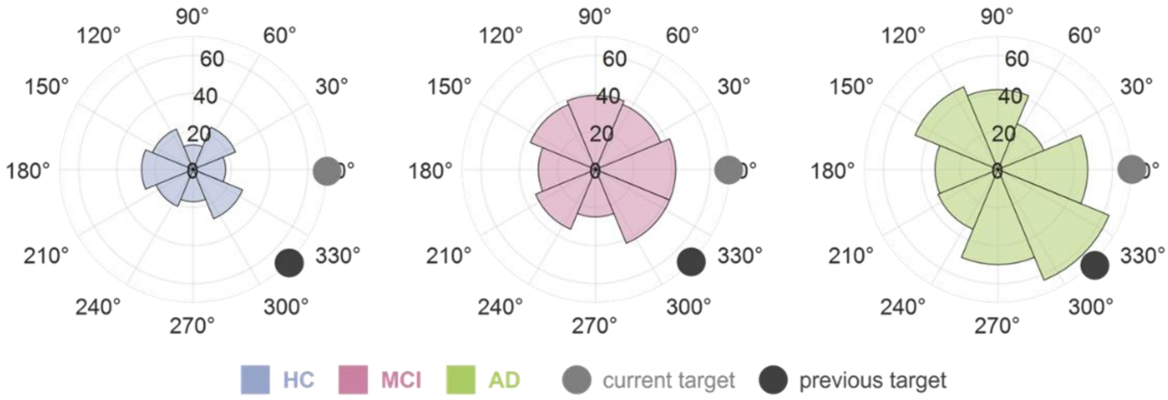

Figure 14. Polar histograms of anticipation direction across all trials for each group. The current target (light grey) is set at 0°, while the previous target (dark grey) is at 345°.

3.3.2 Catching task parameters

Qualitative differences among the three groups of subjects were first explored by visually comparing controller's paths. Figure 15 illustrates speed profiles from three exemplary subjects – one for each group – aligned to the onset time of each trial. Notably, a general reduction in speed was observed in the condition lacking both the thrower and the influence of gravity, suggesting that the absence of external cues may impact the dynamism of movement execution. This reduction was most evident in the AD subjects, whose movements appeared slower and more irregular, reflecting potential motor planning or execution deficits.

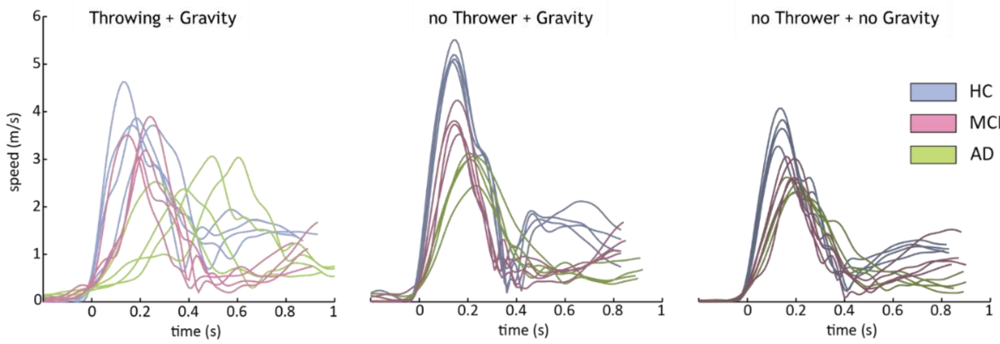

Figure 15. Speed profiles of three exemplary subjects, one for each group (with its specific color), differentiated based on the experimental condition. Each line represents the average among the trials of specific targets.

To determine whether qualitative patterns extended across the full sample, group-level metrics of success rate, reaction time and maximum speed have been examined under each experimental condition.

Task performance across the three groups was first evaluated by analyzing the success rate under different experimental conditions. As shown in Figure 16, significant group differences emerged in the two less naturalistic conditions (i.e., those lacking the thrower), where AD subjects exhibited markedly lower success rates compared to both the HC and MCI groups ($p < 0.001$ and $\beta = -1.12$ for AD-HC and $p < 0.01$ and $\beta = -0.8$ for AD-MCI in no-thrower-gravity condition; $p < 0.001$ and $\beta = -0.91$ for AD-HC and $p < 0.01$ and $\beta = -0.82$ for AD-MCI in no-thrower-gravity condition). These findings indicate that when external cues are removed, individuals with AD struggle more to successfully complete the task. Interestingly, in the most naturalistic condition – featuring both the presence of the thrower and gravity – no significant differences were observed among the three groups.

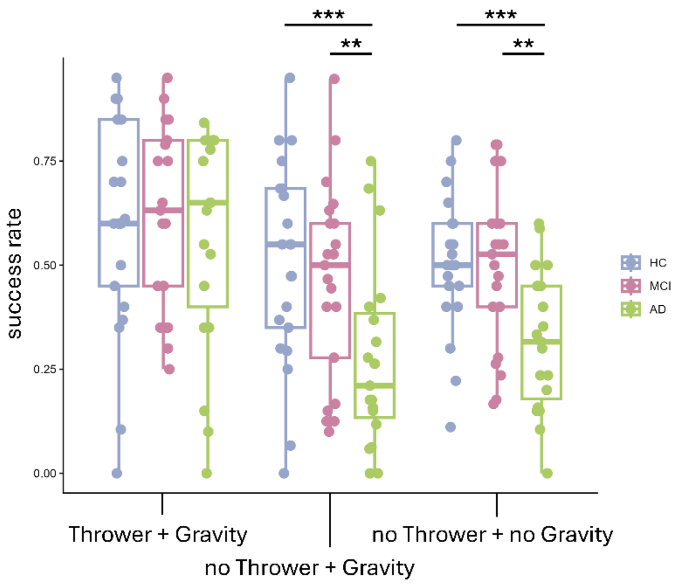

Figure 16. Success rate of the three groups, differentiated by experimental conditions. For each group and condition, the boxplot indicates the distribution of success rates, while each point represents a single subject.

To further investigate cognitive and motor processing, reaction times were analyzed across all groups and conditions. Contrary to initial expectations, no statistically significant differences in reaction time were detected between groups (Figure 17). However, a consistent effect of experimental condition was observed across all groups: the most naturalistic condition (i.e., the one featuring both the thrower and gravity) was associated with the shortest reaction times ($p < 0.001$ and $\beta = 0.1$ with respect to no-thrower-gravity; $p < 0.001$ and $\beta = 0.13$ with respect to no-thrower-no-gravity).

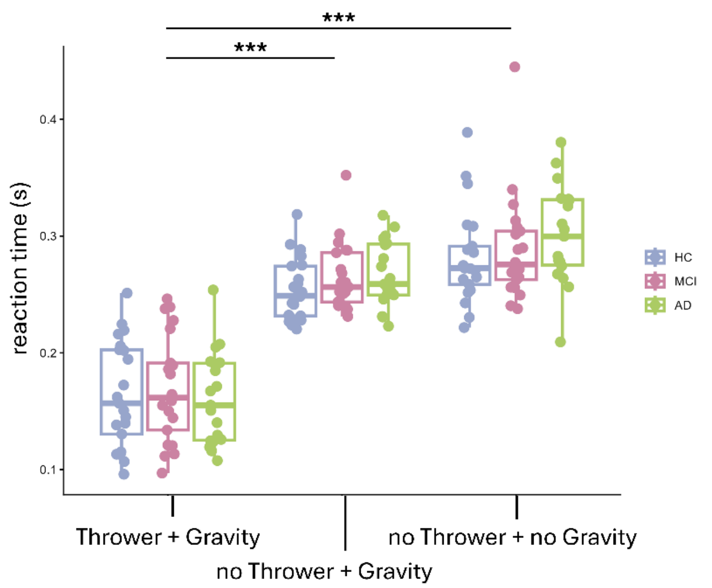

Figure 17. Reaction time of the three groups, differentiated by experimental conditions. For each group and condition, the boxplot indicates the distribution of reaction times, while each point represents a single subject.

In contrast to reaction time, maximum speed values revealed more pronounced group differences. As shown in Figure 18, HC participants achieved higher peak speeds compared to both MCI and AD groups across all experimental conditions, with statistically significant differences between AD and the other two groups ($p < 0.001$ for HC-AD in no-thrower conditions, $p < 0.01$ for the other significant cases).

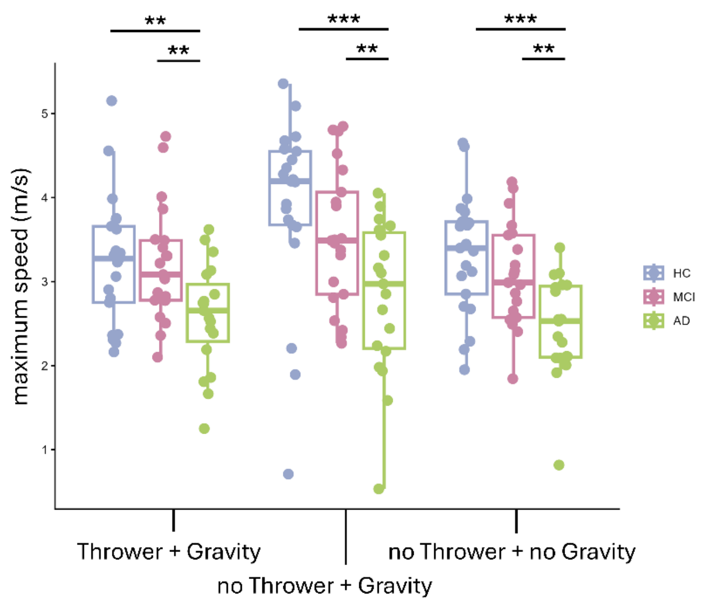

Figure 18. Maximum speed of the three groups, differentiated by experimental conditions. For each group and condition, the boxplot indicates the distribution of maximum speeds, while each point represents a single subject.

3.3.3 LDA classification

The LDA model achieved an overall classification accuracy of 56.7% under LOSO cross-validation. Class-specific performance varied across diagnostic groups. HC were classified with the highest sensitivity (66.7%), followed by AD (57.9%), while classification performance for MCI was the lowest (45.0%). Misclassifications occurred most frequently between MCI and AD, with 30% of MCI cases predicted as AD, but also 26.3% of AD cases predicted as HC. A smaller proportion of HC participants were misclassified as MCI (23.8%) or AD (9.5%).

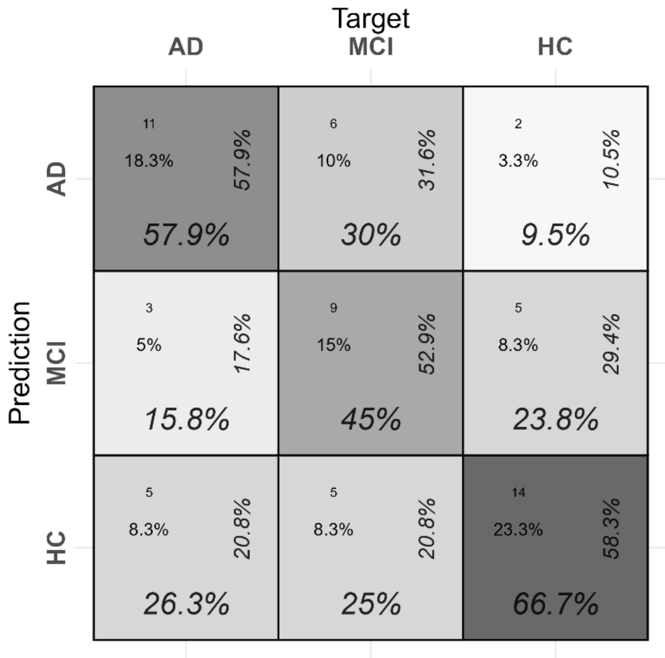

Figure 19. Confusion matrix of LDA predictions obtained with LOSO cross-validation. Rows represent predicted classes, and columns represent true classes. Values inside the cells indicate absolute counts (left smaller), classification percentages (left larger), and row/column percentages (right/bottom).

3.4 Discussion

Results demonstrate that the analyzed metrics can discriminate healthy individuals from cognitively impaired participants. They also show a progressive deterioration of motor performance across healthy aging, MCI, and AD, shaped both by cognitive status and task context, aligned with H2. Across reaching and catching tasks, healthy controls exhibited faster and more accurate movements, whereas MCI and AD participants showed slower trajectories, reduced success rates, and more anticipatory behavior. This pattern aligns with a continuum model of motor decline, suggesting that subtle impairments in motor execution emerge early and worsen with cognitive decline [202], [203].

Interestingly, the two tasks captured different facets of motor-cognitive functioning. Success rate analysis revealed a clear pattern of group differences, but these differences were modulated by task and environmental cues. In the reaching task, success rates followed the expected cognitive gradient (HC > MCI > AD), reflecting the sensitivity of internally guided, goal-directed movements to cognitive decline. A similar gradient emerged in the catching task when the virtual thrower was absent, indicating that unpredictable or low-cue environments disproportionately challenge individuals with AD. However, when the thrower was present, success rates became comparable across groups, suggesting that ecologically valid contextual information can compensate for underlying deficits, particularly in AD. This pattern highlights that success rate is influenced not only by cognitive status but also by task naturalism and environmental support, suggesting that the removal of external cues exacerbates motor planning and execution difficulties, in line with previous findings showing increased reliance on environmental scaffolding in dementia [204], [205]. The improvement in reaching success across repetitions in HC – likely facilitated by the predictable target order – further indicates a learning effect that is substantially reduced in MCI and AD, underscoring not only their motor impairments but also their difficulties in motor learning and motor plan updating [182].

Reaction time analysis provided additional insight into the underlying cognitive and sensorimotor mechanisms and clearly distinguished the two task types. In reaching, reaction times followed the cognitive gradient (HC < MCI < AD), suggesting that internally generated movement initiation is compromised even in early stages of decline, consistent with prior research [206], [207], [208], [209]. In contrast, catching reaction times did not differ significantly between groups but varied systematically across experimental conditions, with the fastest reactions in presence of the thrower. This indicates that externally triggered reactive movements depend more on the availability of sensory cues than on cognitive status, and that environmental information can partially compensate for slower motor planning in cognitively impaired individuals. Moreover, the alignment between reaction time modulation and success rate patterns reinforces the tight link between efficient response initiation and task performance, further illustrating task-dependent modulation of motor deficits.

Finally, maximum speed analysis revealed that peak velocities were significantly lower in MCI and AD compared to HC, likely reflecting a compensatory strategy to preserve accuracy under conditions of impaired motor control [210], [211], [212], [213]. In particular, for MCI, this indicates that alterations in motor execution emerge early, before full clinical dementia onset. Unlike success rate or reaction time, peak velocity was less affected by task naturalism, suggesting that it reflects fundamental neuromotor and cognitive constraints rather than context-dependent facilitation. This finding supports movement speed as a robust marker of motor deterioration, relatively independent of environmental cues and experimental context. The partial independence of peak velocity from environmental cues does not contradict the hypothesized task-dependent effects but rather refine their interpretation by suggesting that some kinematic parameters reflect stable neuromotor constraints while others are more sensitive to contextual modulation.

All these results suggest a gradual continuum of motor deterioration across healthy aging, MCI, and AD. While the most pronounced impairments were observed in AD, intermediate deficits in MCI point to the potential utility of motor assessments as early indicators of pathological cognitive decline. The combination of lower success rates, slower reaction times, and diminished movement speed may constitute a sensitive profile of motor alterations associated with cognitive impairment. Notably, although the MCI group generally showed intermediate values, their behavior did not always differ significantly from the other groups, suggesting that motor deterioration in this pre-dementia stage is subtle and highly variable across individuals. This pattern is consistent with the well-documented heterogeneity of motor dysfunction in MCI populations [178], [210], [214], [215].

Results also highlight two further considerations. First, rehabilitation and assessment tasks should be designed with high ecological validity, as realistic cues may support more successful and efficient movement execution in individuals with AD. The attenuation of group differences in supported conditions demonstrates that environmental scaffolding can mitigate performance deficits, emphasizing the importance of task design in both clinical assessment and intervention. Second, VR provides a powerful tool for creating controlled yet unusual scenarios capable of eliciting behavioral responses and revealing differences that would be difficult to observe in real-world settings. The ability of VR-based metrics in discriminating groups highlights their potential as early biomarkers while acknowledging the need for complementary measures to enhance diagnostic specificity.

Anticipatory behavior analysis offered additional insights into motor planning and executive control. AD participants exhibited increased anticipatory responses, suggesting impaired inhibitory control and disrupted motor planning [170]. Furthermore, higher anticipation rates in early task blocks indicate that these participants initially struggle to perform the task, with limited adaptation over time [216]. MCI displayed a greater number of anticipatory responses than HC but maintained comparable success rates, consistent with early-stage cognitive and motor impairment. The inverse relationship between anticipation and success rates emphasizes that excessive anticipatory movements (likely due to reduced inhibitory control) negatively impact performance. Moreover, higher MMSE scores were associated with lower anticipation rates, reinforcing the link between cognitive decline and motor control deficits. Directional analysis further illuminated impairments in motor learning and planning: AD participants tended to aim toward the previous target during anticipatory movements, a behavior absent in the other two groups. This suggests that, in AD, inhibitory control deficits are accompanied by impaired motor sequence learning, resulting in reliance on previously executed motor plans and reduced adaptability to new task demands. In contrast, HC participants exhibited context-appropriate adjustments, reflecting intact cognitive flexibility and motor learning. Together, these findings underscore how cognitive decline in AD affects both the execution of motor plans and the ability to anticipate and adapt to task sequences, while MCI represents an intermediate stage with subtler and more variable deficits.

Finally, the Linear Discriminant Analysis showed that motor and behavioral features extracted in immersive VR could partially discriminate between groups. Healthy individuals were reliably distinguished from impaired participants, whereas MCI and AD overlapped substantially, reflecting the heterogeneous and gradual progression of cognitive decline [217]. This aligns with the behavioral findings: gross motor deficits can separate healthy subjects from impaired participants, but more subtle task- and context-specific measures are needed to differentiate early stages of decline.

Together, all these findings support a continuum of motor deterioration across healthy aging, MCI, and AD. They also illustrate the complementary insights provided by multiple tasks: reaching task reveals deficits in internally guided planning, reaction time, and inhibitory control, whereas catching task reveals the modulatory role of sensory context and ecological cues in motor execution, demonstrating that motor deficits are modulated by task structure and environmental support. This nuanced understanding has practical implications for early detection, assessment, and rehabilitation, suggesting that ecologically valid, context-rich tasks can both expose subtle impairments and support performance in cognitively impaired individuals. Anticipatory impairments further characterize motor behavior in AD and MCI. Hence, VR-based metrics show promise as sensitive markers of motor change, albeit with limitations in discriminating between intermediate clinical stages.

3.5 Conclusions

This study represents one of the first systematic investigations of motor behavior along the AD continuum within a VR environment. VR provides an innovative and quantitative platform that enables precise assessment of multiple motor parameters in a controlled yet ecologically valid context. Beyond its feasibility, the novelty of this work lies in the integration of immersive scenarios with quantitative kinematic biomarkers, transforming VR from a training tool into a structured assessment framework for motor phenotyping along the AD spectrum. The immersive nature of VR allows the creation of tasks that incorporate naturalistic cues, such as a thrower or gravitational forces in catching tasks, which were shown to enhance performance, particularly among AD participants. This demonstrates that motor execution is influenced not only by intrinsic neuromotor capabilities but also by the sensory and cognitive context in which movements occur, emphasizing the importance of task design in both research and clinical applications.

While these results are promising, several limitations should be noted. The study was conducted in a controlled laboratory environment, so the ecological validity of VR-based assessments and interventions in real-life or home-based settings remains to be tested. Additionally, only specific motor tasks were analyzed, leaving other functional movements and complex motor behaviors unexplored. Finally, the analyses focused on observable kinematic parameters, such as velocity, accuracy, and anticipatory behavior, without incorporating complementary neurophysiological or muscular measures that could provide deeper insights into the underlying mechanisms. Future research integrating multimodal physiological data could extend this framework toward a more comprehensive system-level characterization of motor adaptation in AD.

Despite these limitations, VR proved to be a highly engaging and motivating platform, with participants reporting enjoyment and high compliance during tasks. Its adaptability allows for the creation of scalable, ecologically valid protocols that can be deployed in both laboratory and home-based settings, opening the door to telerehabilitation programs aimed at maintaining motor and cognitive function over time. Moreover, the precision, standardization, and repeatability of VR-based assessments reduce measurement variability, increasing sensitivity for detecting subtle motor alterations along the AD continuum. By coupling ecological immersion with quantitative rigor, this approach advances current assessment methodologies beyond descriptive performance measures toward context-sensitive motor biomarkers. By integrating quantitative motor measures within immersive, realistic, and customizable scenarios, VR aligns closely with the broader goals of this thesis, which focus on leveraging innovative technologies to study and support human motor function in collaborative and clinical contexts.

Overall, these findings reinforce VR's potential as both a research and clinical tool, offering engaging, scalable, and precise approaches for the assessment, monitoring, and rehabilitation of motor and cognitive decline across the spectrum from healthy aging to AD. Importantly, the ability to detect graded differences across groups and their modulation by task context supports the use of VR-based kinematic assessment as a sensitive approach to capture alterations in motor behavior associated with neurodegenerative progression.

4

Postural and multimodal analyses of the impact of Human-Robot Collaboration tasks

This chapter examines how Human–Robot Collaboration (HRC) affects human performance, with particular emphasis on postural and multimodal analyses as quantitative indicators of ergonomic and cognitive–motor adaptation in collaborative industrial environments. Within the framework of the central hypothesis of this thesis, HRC is conceptualized as a structured experimental perturbation of interaction dynamics, eliciting adaptive responses in human behavior. Accordingly, through two complementary studies, this chapter investigates how interacting with collaborative robots shapes postural and cognitive-motor patterns, enabling the quantitative characterization of adaptive strategies in HRC settings.

Section 4.1 outlines the motivations and industrial significance of this research, discussing challenges associated with an ageing workforce and the rising incidence of work-related musculoskeletal disorders. These considerations underscore the need for ergonomic, human-centered solutions in modern manufacturing.

Section 4.2 describes the first study, which investigates postural control during collaborative manipulation with a robot. By combining linear and nonlinear analyses of center of pressure metrics, this study shows how a collaborative robot's presence and behavior affect human balance, offering new insights into postural adaptation and ergonomic implications in HRC scenarios.

Section 4.3 presents the second study, which adopts a multimodal approach to examine human adaptation in collaborative tasks. Expanding on the postural findings of the previous section, it integrates postural metrics, kinematic measures, surface electromyography, and gaze data to characterize the interplay between physical effort, cognitive demand, and task dynamics in HRC.

Both studies follow a consistent structure to facilitate clarity and comparability. Each begins with background and specific research questions, followed by a detailed description of participants, experimental setup, instrumentation, and data analysis. Results sections report the main quantitative findings, while the discussions interpret them considering existing literature and their implications for HRC. Each study concludes with a summary of key insights, limitations, and directions for future work.

4.1 Motivation and industrial relevance

The workforce in the 21st century is characterized by ageing [218]. The increasing duration of working life and the ageing workforce increases the likelihood of people working in their older age with potential diseases and disabilities, some of which are known to increase the risk of occupational injury [219]. For example, studies indicate that over 50% of adults aged 65 and older suffer from some form of musculoskeletal disorders (MSDs) [220], [221], significantly affecting their quality of life and overall health [220], [221], [222], [223], [224], [225], [226], [227]. Thus, understanding the prevalence of MSDs and their associated factors is crucial to developing effective preventive and management strategies [228].

MSDs include various conditions, including osteoarthritis, rheumatoid arthritis, and various forms of musculoskeletal pain, which collectively contribute to reduced mobility, increased disability, and a greater dependency on healthcare services [229]. With the global population aging, the prevalence of MSDs among older adults is expected to increase [228], [230]. Moreover, MSDs have a particularly high prevalence observed in populations with a history of physically demanding occupations [228], especially with jobs frequently involving highly repetitive, short-cycle operations in assembly processes [231]. Work-related MSDs are a major concern in industries where manual labor and repetitive motions are prevalent, potentially leading to chronic pain, reduced productivity, and long-term health problems [150], [232].

Consequently, modern industry must rely on older workers to remain competitive in the global marketplace while safeguarding their well-being [233]. To address the decline in workers' physical abilities and sustain their participation in the workforce, industries can create more supportive environments – for example, through the introduction of collaborative robots (cobots) [231], [234]. Traditionally, industrial robots are integrated to execute repetitive, high-precision, and labor-intensive tasks tirelessly, thereby reducing errors, minimizing costs, and improving product quality [235]. However, despite these advantages, many industrial tasks still rely on human adaptability, creativity, and flexibility – capabilities that cannot be fully automated [236]. This need for balancing automation with human expertise has fueled the rise of cobots, which are specifically designed to support rather than replace human operators [237], [238]. Cobots can assist in physically demanding or ergonomically challenging activities, reducing biomechanical overload while promoting safer and more sustainable working conditions [239]. Their role reflects a broader shift from automation – that isolates humans – to collaboration that actively leverages the complementary strengths of humans and machines. Cobots represent a natural evolution in industrial automation, developed to meet the growing challenges of modern industry, where productivity and quality must increase alongside greater attention to workers' health, safety, and well-being [240].

Human-Robot Collaboration is thus becoming an essential area of focus in the smart manufacturing industry [241]. HRC refers to environments in which humans and robots come into contact forming a tightly coupled dynamic system to perform a task [141], [242], [243]. By combining the complementary strength of both agents (i.e., robotic precision, repetition, and strength [244] with human dexterity, decision-making and adaptive problem-solving [245]), HRC optimizes manufacturing processes [241]. Through the reallocation of repetitive or hazardous tasks to robots, workers can focus on activities that require higher-level judgment and fine motor skills [246].

However, successful collaboration extends beyond productivity and efficiency: it fundamentally depends on human factors that determine whether the interaction is safe, effective, and acceptable in practice [247]. The success of HRC therefore hinges on how operators respond physically, cognitively, and perceptually to shared tasks with cobots. Understanding these responses is essential not only to ensure safety and ergonomics but also to optimize performance and sustain operator well-being in industrial collaborative environments. Evaluating physical and mental demands in collaborative settings has been highlighted as a key factor [149], as ergonomic risk factors and comfort directly impact workers' long-term health [158], [248].

Although the literature has extensively examined the psychological, cognitive, and physical dimensions of HRC, a clear connection between these conceptual frameworks and rigorous experimental evidence is still lacking. In particular, the effects of HRC on postural stability, attentional resources, and fine motor control remain insufficiently explored. Furthermore, most existing studies tend to address motor or perceptual aspects in isolation, rather than employing integrated, multimodal approaches capable of capturing the complexity of real industrial environments.

This chapter aims to address these gaps through two complementary studies. The first investigates how HRC influences postural behavior by analyzing center of pressure dynamics. The second adopts a broader experimental approach, combining physiological, cognitive, and behavioral measures with postural data. This multimodal perspective enables a more comprehensive understanding of operator responses in HRC, offering deeper insights into workload, attention, and adaptation. Ultimately, the goal is to provide evidence-based guidelines for designing collaborative workspaces that enhance both performance and well-being.

4.2 Postural analysis in HRC tasks

4.2.1 Background

Postural analysis represents a fundamental approach to quantify human adaptation during collaborative tasks, as it provides insights into how individuals maintain stability while interacting with dynamic environments or external agents. When work tasks are performed in quasi-static conditions, direct measures of posture could reveal insights into the stability and balance of workers and can thus be used to improve ergonomics during HRC [249]. Poor or sustained postures can cause musculoskeletal imbalances, increased strain on joints and muscles, and altered movement patterns over time [250]. Indeed, MSDs may arise due to improper postures or behaviors [251]. Posturography data could help evaluate musculoskeletal load, identify ergonomic risk factors, and develop strategies to mitigate them.

Traditionally, sensorimotor and cognitive mechanisms involved in balance control are studied using conventional center of pressure (COP) measures. COP represents the point where the resultant ground reaction force is applied during standing or movement, and its displacement over time provides valuable insights into postural stability and balance. Standard COP metrics include mean amplitude and mean distance (reflecting the extent of the postural sway), mean velocity (representing the speed of postural adjustments), and confidence ellipse area and sway area (characterizing the distribution of the sway) [10]. These parameters are crucial for understanding how the body maintains equilibrium, particularly during tasks that involve dynamic movement or changes in posture. Additionally, variations in COP data can help identify deviations from normal posture, which may indicate potential risks for musculoskeletal discomfort or injury.

However, some researchers have argued that traditional analyses of the spatial dynamics of postural activity are not sufficient to fully understand the mechanisms underlying postural control and, in particular, cannot provide a complete understanding of stability and instability in the control of posture [252], [253], [254]. These measures offer an overall view of postural sway and may be linked to the adopted muscular strategy, but they do not directly refer to the adopted control strategy or to the attentional demand allocated to the control of balance. Specifically, these traditional parameters primarily focus on linear characteristics of postural control and may not fully capture the complexity of human balance regulation. They mainly quantify the magnitude and spatial extent of postural sway, describing how far or how fast the COP moves but they do not capture how postural adjustments are organized over time. Consequently, two conditions may exhibit similar sway amplitudes while relying on different balance control mechanisms, such as more automated or more exploratory regulation. For this reason, nonlinear approaches have increasingly been introduced to complement classical COP metrics by characterizing the temporal structure and regularity of postural fluctuations, thereby offering a more comprehensive perspective on postural dynamics [255].

Deepening the understanding of the mode of control and of its underlying mechanisms has encouraged researchers to call for more powerful and relevant techniques of analysis [256].

Among the indicators recently introduced to capture distinct aspects of the nonlinear temporal dynamics of time series data, Recurrence Quantification Analysis (RQA) has been hypothesized as a viable methodology to capture aspects linked to balance maintenance [257], [258], [259], [260], [261], [262], [263]. RQA describes the temporal structure of a dynamic system by quantifying the number and duration of repeated states [264]. Crucially, RQA does not merely describe the magnitude or variability of movement – as traditional COP metrics do – but instead reveals how postural adjustments evolve over time. This includes capturing aspects such as the repetitiveness of the displacement trajectory, the complexity of the control strategy, and the system's predictability or adaptability [255], also in conditions where balance maintenance is challenged by the presence of repetitive supra-postural tasks [265]. Some of the most commonly used RQA parameters are the relative amount of recurrence and determinism [255].

Hence, traditional COP parameters offer a general overview of gesture characteristics, while RQA provides complementary insight by capturing the temporal structure and regularity of postural adjustments. Accordingly, this study combines both types of metrics to assess postural control and biomechanical risk during the execution of manipulatory tasks performed with and without robotic assistance. The experimental task followed a structured sequence consisting of rest, object grasping, object manipulation, object release, and rest. This analysis focused only on the manipulation phase, that is when the subject actively interacted with the object, while grasping, release, and rest periods were excluded. This approach allows for a specific assessment of postural control precisely during sustained object handling. Unlike previous studies [249], [266] which focused on sequential task execution with a cobot, this work examines two parallel task configurations, where the human and the cobot interact simultaneously. This introduces a fundamentally different interaction dynamics, where HRC is performed with robots and humans sharing the same space and concurring on the same task [267].

Accordingly, the goal of this work is twofold: first, to investigate whether the assistance of the collaborative robot influences postural control and musculoskeletal load compared to performing the task alone; and second, to explore whether varying the mode of robotic collaboration within parallel tasks elicits distinct biomechanical responses. Robotic assistance is hypothesized to increase postural demands, with different modes of robotic collaboration eliciting distinct postural responses, indicating context-dependent interactional adaptations. Furthermore, linear and nonlinear measures are assumed to capture complementary aspects of these effects, providing converging yet non-redundant information on postural and interactional dynamics. Ultimately, this approach aims to facilitate real-time monitoring of workers' physical strain and supports the development of ergonomic strategies to reduce MSDs and enhance workplace safety.

4.2.2 Materials and methods

Participants

Fourteen healthy right-handed male subjects took part in the study (age: 26 ± 3 years; height: 177 ± 6 cm; weight: 71 ± 7 kg). Subjects were recruited based on their non-familiarity with the task and the absence of any known musculoskeletal, neurological, or visual impairment. Prior to participation, all subjects provided informed consent, and the study was approved by the institutional ethics committee.

Experimental setup

The experimental setup was designed using a 2x1 m table on which a collaborative robot (Franka Emika Panda, Munchen, Germany) was positioned opposite to the subject, who stood in an upright posture, to simulate a collaborative workbench environment. Participants were instructed to cyclically perform a manipulation task using a custom-designed tool (Figure 20), specifically developed to simulate common and functionally relevant manipulation activities. It was a wooden beam equipped with four interactive mechanisms: a white knob, a rotatory component with a high-positioned orange knob, a black padded section designed for grip, and a white lever mounted on a rectangular structure.

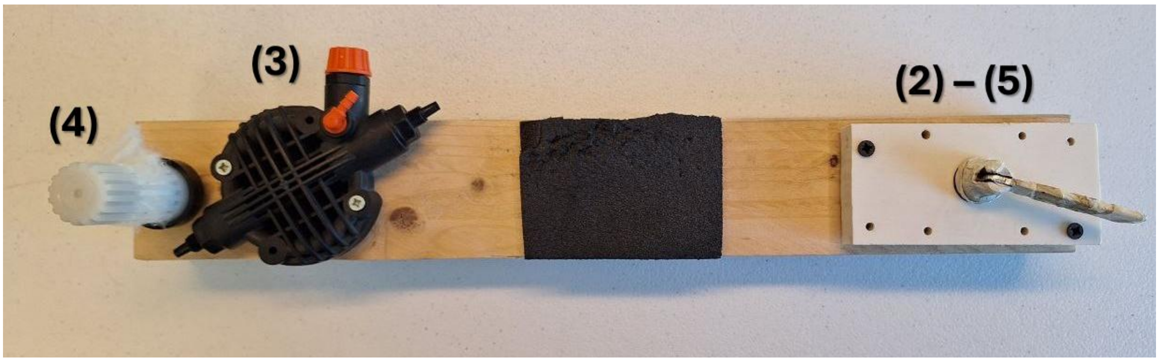

Figure 20. Object designed to be manipulated in the task. The numbered labels identify the items to be manipulated at each corresponding step of the task sequence.

Two 6-component force platforms (BTS P-6000, BTS Bioengineering, Milan, Italy) were positioned under the subjects' feet to record ground reaction forces and to derive COP coordinates. Force data were collected at a sampling frequency of 500 Hz. Each platform was positioned under one foot. Additionally, a marker-based optoelectronic system (BTS SMART-DX 6000, BTS Bioengineering, Milan, Italy) was employed to segment and identify each task repetition, with passive markers placed at key anatomical landmarks. These kinematic data were acquired using a sampling frequency of 250 Hz, and force platforms data were then resampled at the same rate.

Experimental protocol

The manipulation task consisted of the following steps: (1) take the object, (2) open the lever on the right by rotating it 90° counterclockwise, (3) rotate the high-positioned orange knob until it reaches the end of its stroke, (4) unscrew the white knob on the left for two full turns, (5) close the lever that was opened at step 2, and (6) return the object to its original position. After completing this sequence, subjects rested with their arms at their sides. Following a brief pause, they independently decided when to initiate the next cycle of manipulation. The experiment included three conditions:

- Free (F). The subject performed the task independently. The object was positioned on an elevated support on the right side of the table for easy access. Using their right hand, the subject grasped the object and executed a predefined sequence of movements. The task was considered complete once the object was returned to its initial position.
- Robot Free (RF). The cobot assisted the subject by securely holding the object at its central part, simulating a "gravity compensation" condition thus minimizing the load the subject was required to support. In this condition, the cobot could move freely in response to the subject's needs. The task began with the cobot holding the object, after which the subject approached and performed the required sequence of movements. The task ended when the subject guided the cobot back to its starting point on their right.
- Robot Plane (RP). Similar to RF, the cobot securely held the object at its central part. However, in this condition, the robot's movement was constrained to a virtual horizontal plane, locking the object vertical movement and allowing free movement in other directions. The task shared the same starting and ending configurations as the Robot Free condition. The height of the simulated plane was kept fixed for all the experiments, regardless of the subject.

The inclusion of two distinct robot-assisted conditions was motivated by the hypothesis that varying the mode of collaboration could elicit different effects on human motor behavior and postural control. Specifically, the RP condition implements a gravity-compensation scenario in which the object is virtually weightless and its vertical position is fixed. This constraint results in a different interaction with the cobot: while in the RF condition participants need to continuously support and stabilize the cobot with one hand while performing the task with the other, in the RP condition they can rely on the cobot's fixed height, potentially leading to the adoption of different motor strategies. Moreover, the inability to move the robot vertically may require participants to adapt their posture or reposition themselves to comfortably perform specific movements. This distinction between RF and RP thus allows to examine how different kinematic constraints and interaction modes with the cobot influence postural control and task execution. An illustrative photo of an individual performing the task under robot-assisted conditions is shown in Figure 21.

Figure 21. Example of the manipulation task with robotic assistance.

Participants were free to move naturally in all conditions, with the only requirement being the use of their right hand to grasp the object. Each condition was repeated three times, with each trial consisting of five repetitions of the manipulation task. The trials were conducted in a randomized order to minimize potential learning effects and ensure natural task execution.

Data analysis

Trajectories of the COP for each of the lower limbs (i.e., COP-right and COP-left) were extracted from the force plates data. The total COP was then obtained as the weighted average between COP-right and COP-left, and its displacement was defined by both the antero-posterior (AP) and the medial-lateral (ML) coordinates with respect to a reference system centered between the 2 force plates. Cycles of the movement were identified using motion capture data: segmentation was made by detecting the time instant when the marker on the right wrist reached the maximum rightward excursion in the ML direction, indicating the completion of a repetition. Only manipulation phases were extracted for the analysis, as the focus was specifically on these active interactions, excluding the other phases (i.e., rest, object pick-up and object release).

Four COP-derived sway parameters were selected to evaluate postural stability and quantify changes in balance: mean distance (MDIST), mean velocity (MVEL), 95% confidence ellipse area (CE-AREA), and sway area (SW-AREA). These metrics were chosen based on their ability to capture distinct yet complementary aspects of postural control and stability. Mean distance quantifies the extent of postural displacement, reflecting the range of movement and how far the COP deviates from a reference point. Mean velocity measures the speed of postural displacement, indicating how quickly the individual adjusts their posture. Ellipse area captures the spread of the COP, providing insights into postural control by assessing variability and dispersion. This metric was preferred over the confidence circle area, as the elliptical estimate accounts for the directionality of sway – a relevant feature when COP trajectories are not uniformly distributed but follow a predominant path [249]. Sway area provides a measure of the extent of postural instability during task execution. For each cycle of the task repetition in each experimental condition, these parameters were calculated as defined in [267]. Mean values were then computed and subjected to inferential statistical analysis to assess potential differences across conditions.

In addition to these conventional analyses, a Recurrence Quantification Analysis was performed to explore the underlying dynamical patterns of postural sway. This provides insight into the temporal organization, predictability, and adaptability of postural control – aspects that are especially relevant in dynamic and interactive tasks – and are not influenced by subjects' anthropometric characteristics. To investigate dynamics on a cycle-based time reference, time delay has been set to the average length of the cycle evaluated for each trial. The processing steps adopted for extracting the recurrence maps, similar to those used in [266], are reported in Figure 22.

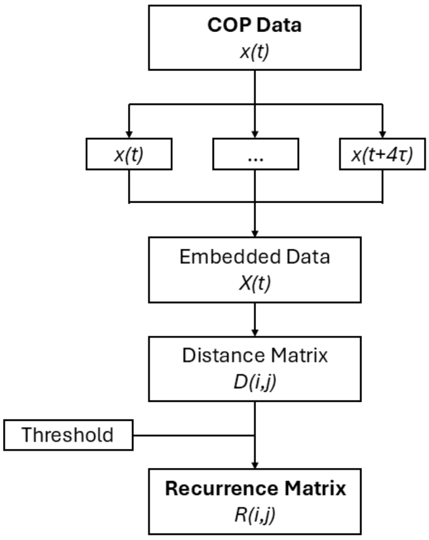

Figure 22. Flowchart for the embedding of COP data and the extraction of the recurrence matrix.

RQA was carried out on the radial component of the COP, as well as on the AP and ML components alone. Specifically, three parameters were calculated to analyze the dynamics of postural sway [266]. The recurrence rate (REC), also known as the density of recurrence points in the recurrence plot [255], quantifies the percentage of recurrent states in the COP trajectory, reflecting the overall stability of postural sway. The determinism (DET) indicates the proportion of those recurrence points that form structured diagonal lines, which is associated with the predictability and regularity of sway patterns. Finally, the ratio between DET and REC represents the extent to which the recurring patterns are deterministic in nature.

Statistical analysis

Normality of sway parameters and RQA indicators was assessed using the Shapiro-Wilk test. Since at least one of the distributions of each parameter was not normal, non-parametric statistical analyses were applied. To evaluate differences in both traditional and RQA-based parameters across the three experimental conditions, a Friedman test was performed. When a significant main effect was found, pairwise comparisons were conducted using the Wilcoxon Ranksum test with Bonferroni correction. The significance level was set to 0.05, 0.01 and 0.001 (*, ** and ***, respectively). Effect sizes were calculated to quantify the magnitude of observed differences and are reported as correlation coefficients (r), with thresholds of 0.1–0.3, 0.3–0.5, and >0.5 denoting small, medium, and large effects, respectively.

4.2.3 Results

Linear metrics

Figures 23, 24 and 25 show the COP trajectories of all subjects in the three experimental conditions: Free, Robot Free, and Robot Plane, respectively.

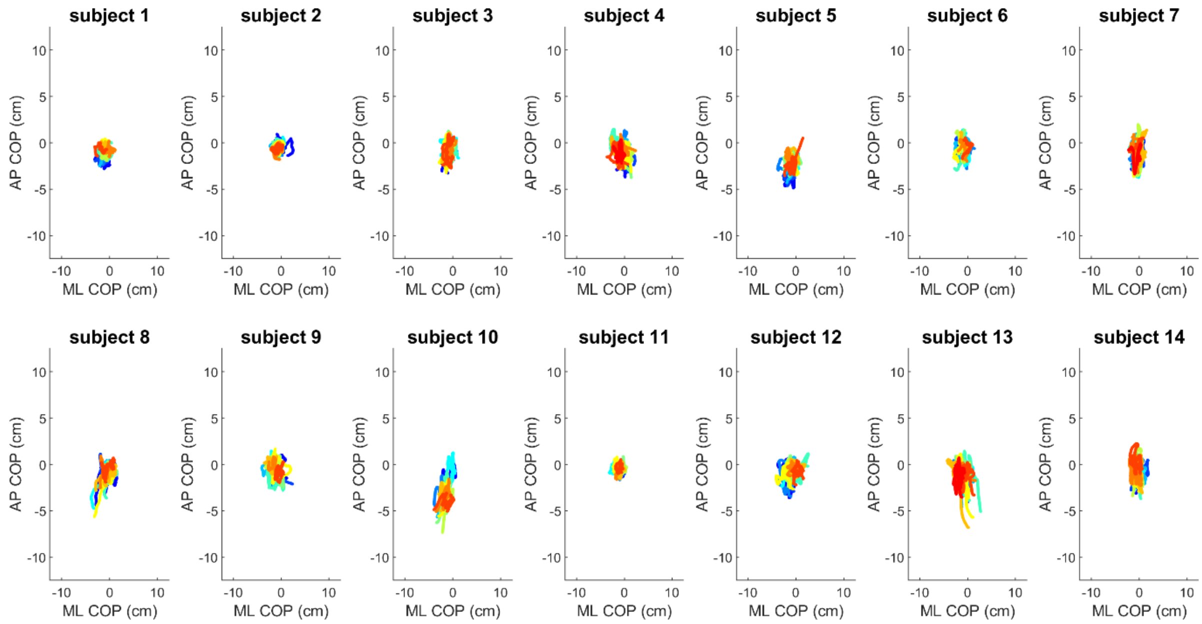

Figure 23. COP trajectories for each subject during the Free experimental condition. Each color is associated with each task repetition.

In the Free condition (Figure 23), COP trajectories exhibit a compact pattern for all subjects, extending roughly 5 cm in both ML and AP directions. Paths remain well-contained within a small spatial envelope, showing limited variability across cycles.

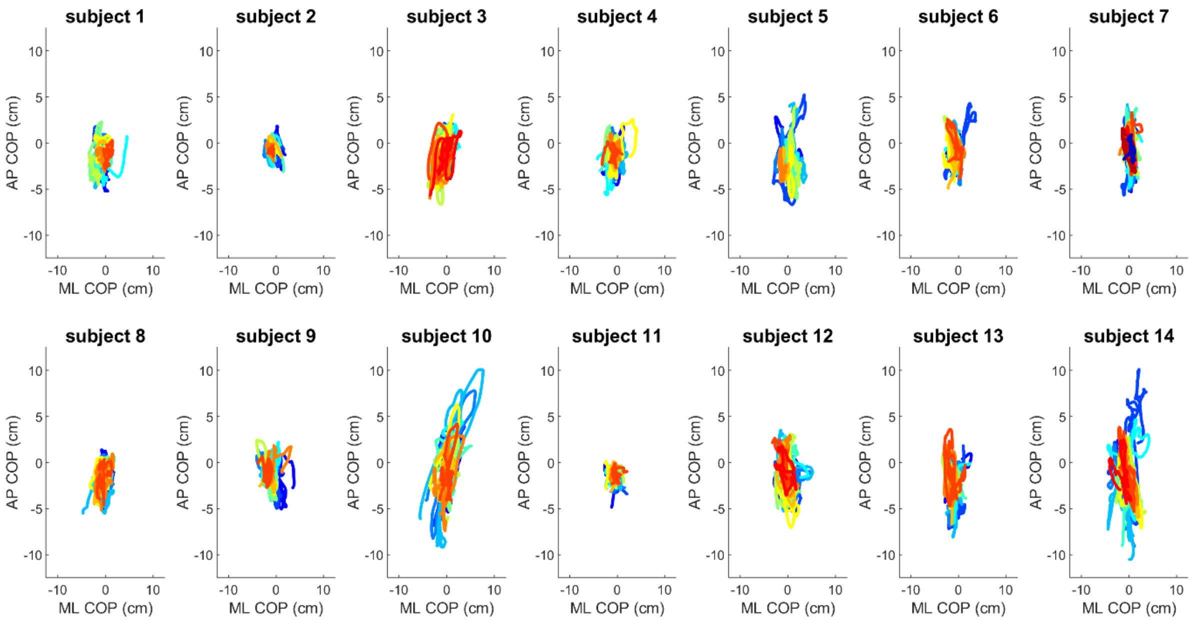

Figure 24. COP trajectories for each subject during the Robot Free experimental condition. Each color is associated with each task repetition.

In the Robot Free condition (Figure 24), COP trajectories display a broader pattern compared to those observed in the Free condition (Figure 23), particularly long with the AP axis. The range of displacement remains confined to around 5 cm in the ML direction but increases to approximately 15 cm in the AP direction. While intra-subject variability across cycles remains limited, greater inter-subject variability in COP patterns is observed, with the greatest extents for subjects 10 and 14.

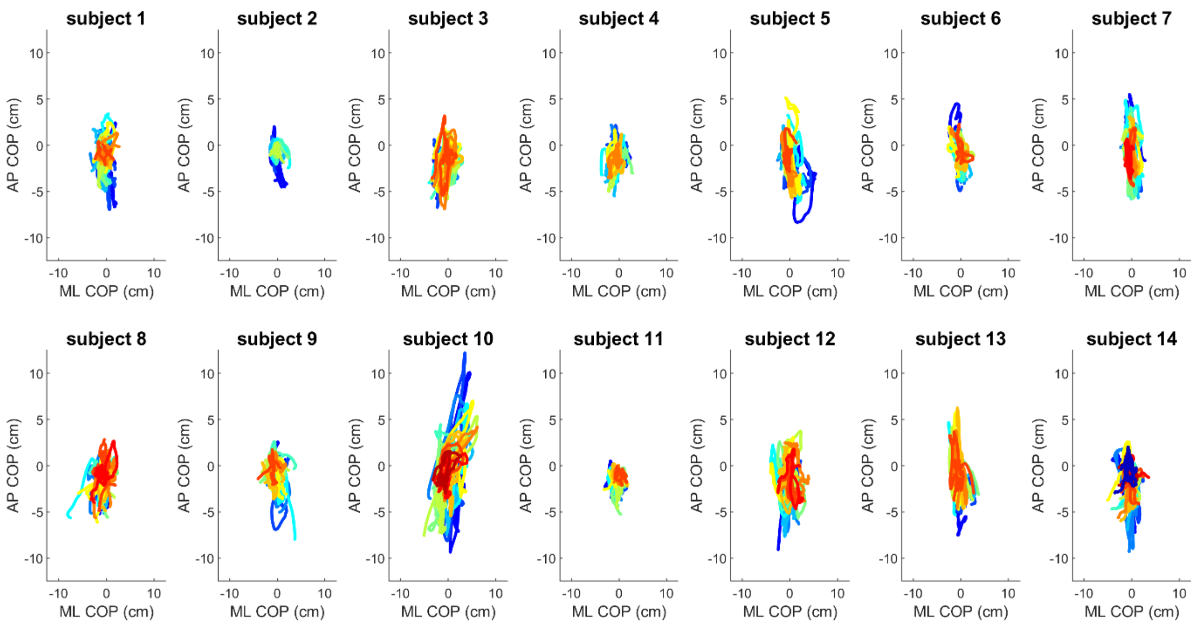

Figure 25. COP trajectories for each subject during the Robot Plane experimental condition. Each color is associated with each task repetition.

Similar to what observed in the Robot Free condition (Figure 24), COP trajectories in the Robot Plane condition (Figure 25) exhibit a broader pattern compared to those in the Free condition (Figure 23), particularly along the AP axis. Displacement in the ML direction remains confined around 5 cm, while in the AP direction it increases to approximately 10 cm. Both intra-subject variability across cycles and inter-subject variability are generally limited, though slightly higher than those observed in the Free condition (Figure 23).

The qualitative differences observed in COP trajectories are supported by the quantitative analysis of sway parameters, as illustrated in Figure 26. Significant increases were found from the Free condition to both robot-assisted conditions, with all parameters showing $p < 0.001$ and $r = 0.88$, while no significant differences emerged between the two robot-assisted conditions.

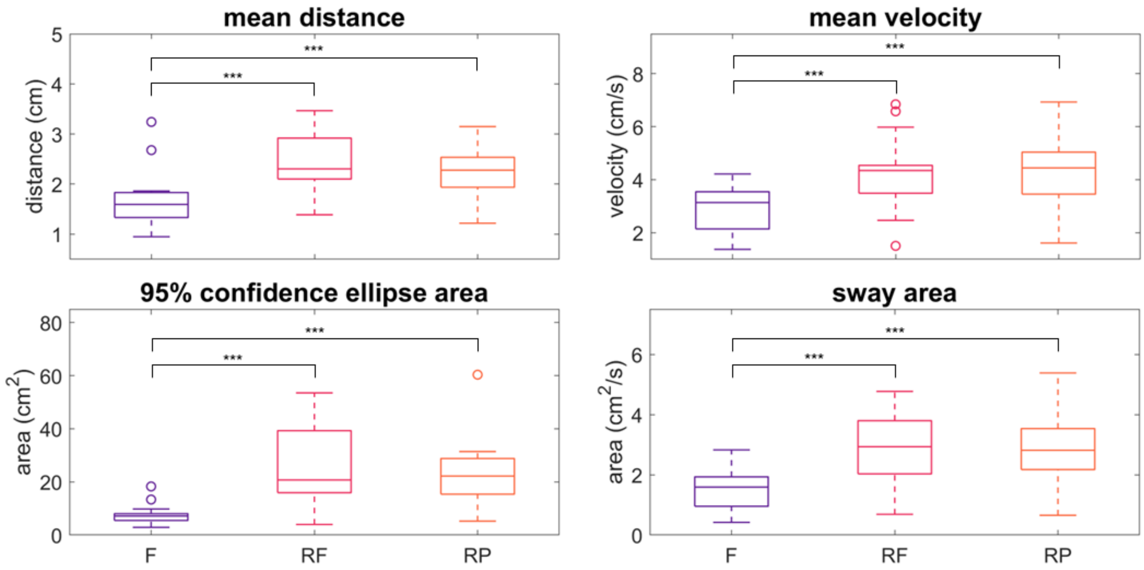

Figure 26. Distribution of sway parameters, differentiated by experimental conditions.

Nonlinear metrics

An example of the RQA recurrence maps obtained from a subset of the cycles relative to one exemplary subject is reported in Figure 27. A consistent pattern emerges across both robot-assisted conditions, marked by a greater density of points along the principal diagonal line in the recurrence maps compared to the Free condition. The Free condition exhibits a more pronounced checkered structure, reflecting the prevalence of recurrent quasi-stationary states.

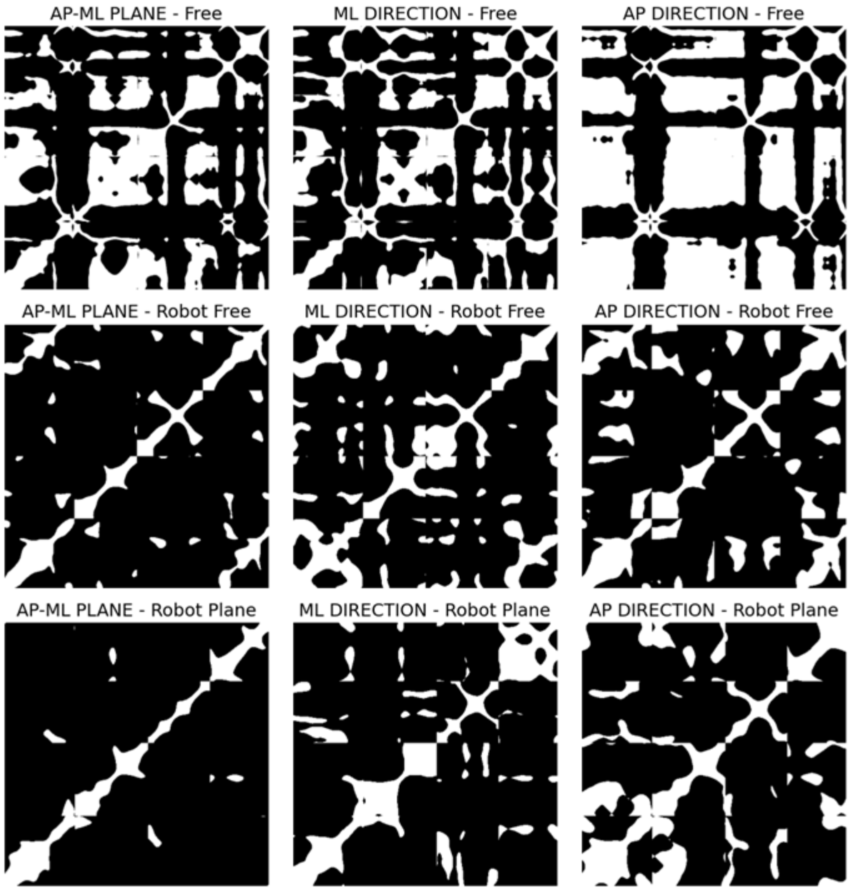

Figure 27. Sample recurrence maps, relative to one exemplary subject, in different trials and for different directions.

These qualitative and specific observations are supported by the quantitative results shown in Figure 28, which presents boxplots of the RQA-based parameters for all subjects. Specifically, recurrence rate (REC) was significantly lower in both robot-assisted conditions across all planes and directions, even though with varying levels of significance. In the AP-ML plane, REC decreased significantly from F to both RF and RP ($p < 0.01$; $r = 0.88$). In the ML direction, REC decreased from F to RF ($p < 0.05$; $r = 0.65$) and from F to RP ($p < 0.05$; $r = 0.75$). In the AP direction, REC also decreased from F to RF ($p < 0.05$; $r = 0.75$) and from F to RP ($p < 0.01$; $r = 0.86$). In contrast, determinism (DET) remained largely unchanged across conditions. Consequently, the DET/REC ratio was significantly higher during robotic assistance, indicating a shift toward more periodic and structured postural control strategies. This ratio increased from F to RF and RP in the AP-ML plane ($p < 0.01$; $r = 0.88$), in the ML direction (F vs. RF: $p < 0.05$; $r = 0.6$; F vs. RP: $p < 0.05$; $r = 0.75$), and in the AP direction (F vs. RF: $p < 0.05$; $r = 0.75$; F vs. RP: $p < 0.01$; $r = 0.86$).

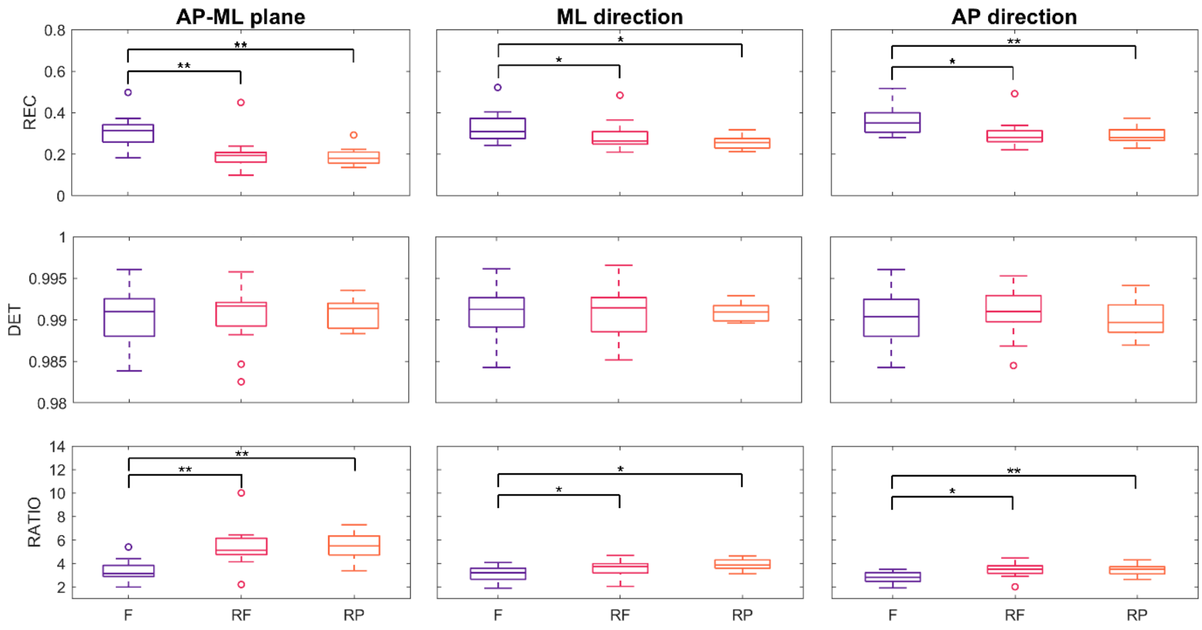

Figure 28. Distribution of RQA parameters, differentiated by experimental conditions.

4.2.4 Discussion

The analysis of the COP trajectories shows a greater extent along the anterior-posterior direction in robot-assisted conditions with respect to the Free condition, possibly indicating a higher number of oscillations of the body when the collaborative robot intervenes in the task execution. This could suggest that subjects tend to deviate from their postural stability, potentially compromising the overall efficiency and coordination of the kinematic chain during task execution. The absence of an evident difference between COP paths in the Robot Free and Robot Plane conditions suggests that the specific mode of collaboration with the cobot does not substantially modulate postural stability, which appears to be primarily influenced by the presence of robotic assistance rather than by the interaction mode itself.

Suggestions resulting from these qualitative observations align with quantitative results from the analysis of traditional COP parameters, which all showed higher values in robot-assisted conditions compared to the Free condition. This overall increase indicates altered postural dynamics induced by robotic assistance, independent of the specific collaboration mode. The rise in mean distance suggests that robot-imposed constraints alter postural stability and strategy, a pattern typically associated with reduced ability to maintain a steady stance [252], diminished postural control [11], and balance impairments [268], [269], [270]. The increase in mean velocity reflects a greater need for active postural regulation, with more frequent adjustments and higher control effort, often linked to instability or heightened postural demands [10], [11], [271]; in this context, however, its simultaneous increase with mean distance suggests not only instability but also a purposeful adaptive strategy to accommodate the collaborative task. The enlargement of the ellipse area indicates broader exploratory sway, likely reflecting an adaptive response to the altered task dynamics introduced by the robot and aligning with patterns associated with reduced balance control

[272] and more difficulty maintaining stability [273]. The increase in sway area further supports this interpretation, as greater sway is generally considered a marker of decreased stability [274].

Contrary to the initial hypothesis, no significant differences emerged between the Robot Free and Robot Plane conditions across all parameters. Although constraining the robot's movement was expected to modulate postural dynamics, the results indicate that the presence of robotic assistance itself, rather than the specific collaboration mode, was the primary factor shaping participant responses. The support provided by the cobot in both conditions appears sufficient to alter task demands and induce comparable adaptations in postural behavior. While alternative experimental designs may have highlighted more subtle distinctions between conditions, these findings nonetheless confirm the central role of robotic assistance in driving postural adaptation.

Overall, COP tends to travel more (higher MVEL and, to a certain extent, SW-AREA) and further (higher MDIST and CE-AREA) when robotic assistance is provided. In general, larger COP excursions are associated with reduced balance control, indicating a decreased ability to remain in a smaller (and typically more stable) area during task repetitions [249]. This may suggest that the cobot influences task execution, which is particularly relevant given that increased COP excursions are associated with the development of MSDs [275]. From this perspective, the Free condition appears to allow the most effective postural control and impose the lowest associated risk, as evidenced by more stable and restricted sway patterns.

These findings might be the result of an alteration of the body schema, an integrated and dynamic internal representation of the body and its surrounding space [276], continuously shaped and updated through sensory and social interactions [277]. Efficient movement in space requires both localizing objects in extra-personal space and maintaining a constantly updated status of body shape and posture [278]. The body schema reflects how the body interacts with its environment, and it is highly plastic, adapting to novel tools or altered body representations [279]. Here, the cobot holding the object may have challenged this schema, leading to difficulty in incorporating cobot interaction and thereby potentially explaining the increased postural sway. Indeed, recent works may suggest that interactions with robots and virtual agents can disrupt or extend embodiment, requiring new sensorimotor adaptations [280], [281], [282], [283], [284], [285].

Nonlinear results further support this interpretation. Lower recurrence rates in robot-assisted conditions may suggest a more variable or exploratory balance strategy, as postural states repeat less frequently. This indicates a shift away from stable, habitual postural control patterns toward more dynamic adjustments, potentially reflecting the fact that the cobot is not yet fully integrated into the participant's body schema. In this context, participants might have needed to continuously recalibrate their posture in response to the actions of the cobot, rather than relying on familiar strategies. This interpretation aligns with the idea that technological artifacts reshape bodily experience and require new sensorimotor adaptations [278], [283], [286], [287]. Notably, recurrence rate values are comparable across the two robot-assisted conditions, suggesting that the mode of interaction does not further alter the degree of postural control. In other words, the presence of the cobot itself introduces a fundamental shift in balance strategy, but the specifics of the interaction mode may have a limited additional effect on this aspect of postural control. Comparable determinism values across all conditions indicate that, despite the increased postural sway and lower recurrence observed in the robot-assisted conditions, the postural responses remain structured rather than random. This suggests that participants are still employing organized control strategies, even if these strategies are more adaptive and less repetitive. This reflects a balance between flexibility and structure: while the presence of the cobot necessitates ongoing adjustments, subjects appear to adopt consistent patterns, rather than reacting in a chaotic or unpredictable manner. This might be related to Black's critique of the "natural" interface assumption [286]: the robot-object system does not immediately integrate as a seamless extension of the body, but does not cause complete instability either. Although the cobot may provide sufficient task stability, its presence is not yet fully integrated into the body schema, requiring continuous movement adjustments while maintaining a coordinated response. However, confirming this interpretation would require long-term longitudinal studies to assess whether such adaptations persist, diminish, or evolve over time.

Importantly, as observed with conventional COP measures, no significant differences were found between the two robot-assisted conditions across all RQA metrics, further indicating that the specific mode of parallel collaboration did not substantially affect overall postural outcomes. RQA findings suggest that interaction with the cobot challenges postural control without introducing randomness in balance control. The presence of the cobot appears to prevent full postural automatization, requiring individuals to engage in ongoing adjustments rather than relying on familiar movement patterns. These results are also consistent with broader research on tool use, which demonstrates that tools can alter both perceptual and motor processes in healthy individuals as well as those with brain damage [276], [278], [287], [288]. Effective tool use involves more than simple physical manipulation: it requires recognizing the object as a tool, knowing how to interact with it, and understanding the outcomes of its use [289], [290]. These processes may be difficult to fully integrate into the body schema, particularly when new dynamics are introduced that the body has not yet adapted to, such as those posed by a collaborative robot.

Therefore, the interpretations derived from linear analyses also extend to nonlinear findings, which further revealed changes in postural dynamics consistent with adaptive balance strategies, highlighting the complementary value of combining linear and nonlinear approaches. While conventional COP parameters mainly describe the magnitude and spatial extent of postural sway, they do not capture how postural control is organized over time. In contrast, RQA revealed that the increased sway observed in robot-assisted conditions reflects structured and coordinated adjustments rather than random fluctuations, providing insight into the temporal dynamics of postural control.

Although this study contributes meaningful evidence regarding the effects of collaborative robots on human postural control, several limitations should be considered when interpreting the results. The research was conducted in a controlled laboratory setting using a standardized manipulation sequence, a simulated workbench, and a custom tool. However, the task sequence was carefully designed to closely resemble typical industrial manipulating operations and allowed to capture key aspects of HRC, such as coordination with a robotic partner, repetitive handling, and precise posture adjustments. Another key limiting factor is the restricted participant sample, which could limit the generalizability of the findings to a broader industrial workforce. However, the large effect sizes indicate that the identified effects are robust and not solely sample dependent, and nonlinear indicators would reasonably be expected to maintain similar variations even in more diverse populations. Moreover, the study focused on short-term cobot interactions, leaving open questions about the long-term effects of repeated exposure, which might influence postural stability and increase the risk of developing musculoskeletal disorders. Finally, attributing the observed alterations in postural dynamics to body schema changes remains hypothetical and requires complementary methods and longitudinal studies to support evidence and strengthen causal inferences. Building on these limitations, future research should broaden task variability, object characteristics, and interaction dynamics, include participants of different ages, sexes, and health conditions, and employ longitudinal multimodal assessments to determine whether repeated exposure leads to lasting adaptations in postural control.

4.2.5 Conclusions

This study examined how HRC influences postural control and musculoskeletal load during dynamic object-manipulation tasks performed in upright stance. Consistent with the broader aims of this thesis, this experiment provides key insights into how the presence of a collaborative robot modifies balance regulation and whole-body stability. Beyond documenting performance differences, the novelty of this study lies in conceptualizing human–robot collaboration as a controlled motor perturbation, enabling quantitative investigation of whole-body adaptive responses rather than solely task-level outcomes. By combining traditional COP-derived linear sway analysis with nonlinear Recurrence Quantification Analysis, the study captured not only the magnitude of postural fluctuations but also the structure of postural dynamics over time. This integrative analytical approach represents a novel methodological contribution, as it moves beyond descriptive sway metrics toward a dynamical systems interpretation of postural regulation in HRC contexts.

Results showed that interacting with the cobot led to increased COP displacement and velocity compared to performing the task alone, indicating greater postural demands and reduced stability [291]. These effects likely arise from the additional constraints introduced by coordinating with the robot, the unpredictability of shared control, and the need for continuous online adjustments to preserve both balance and task accuracy. The nonlinear analysis further revealed lower recurrence rates but stable determinism, suggesting that, even if postural control becomes more variable when working with the cobot, this variability remains organized rather than random – an indicator of adaptive, exploratory stabilization strategies. Importantly, this structured variability supports a reinterpretation of postural alterations in HRC: increased sway should not be understood solely as instability, but as evidence of active reorganization within a complex adaptive motor system. Interestingly, no significant differences emerged between the two robot-assisted conditions, implying that the robot's mere presence is the primary driver of postural alterations.

These findings highlight important ergonomic considerations for the integration of collaborative robots in the workplace. Results highlight that collaborative robotic tasks can affect whole-body postural organization, even when local task execution remains unchanged. This dissociation between local performance and global postural dynamics represents a relevant contribution to HRC evaluation, suggesting that traditional task-performance metrics may underestimate the systemic motor impact of collaboration. This supports the inclusion of postural control and dynamics as complementary indicators in ergonomic assessments of HRC, alongside conventional biomechanical measures. Increased COP excursions have been associated with greater musculoskeletal load and a higher risk of fatigue-related disorders [249], suggesting that poorly designed HRC interactions may unintentionally heighten physical strain. At the same time, the structured variability observed through RQA indicates that humans can adapt their postural strategies to accommodate robotic partners – an encouraging sign for the feasibility of safe, long-term collaboration. These insights reinforce the need for cobot designs and interaction strategies that support, rather than disrupt, natural balance regulation: adaptive assistance, intuitive communication cues, and ergonomically aligned movement behaviors can help ensure that cobots complement human capabilities rather than challenge them.

Overall, this study contributes to the thesis's overarching goal of understanding how emerging technologies shape human motor behavior in collaborative contexts. By integrating linear and nonlinear postural metrics within an experimentally controlled HRC paradigm, this work advances current ergonomic evaluation approaches toward a systems-level assessment of human adaptation in collaborative robotics. By applying advanced quantitative methods to evaluate postural stability during HRC, the results emphasize both the potential benefits and the ergonomic challenges of integrating cobots into dynamic manual tasks. Ensuring that collaborative robots promote stable, efficient, and sustainable human work will be essential for developing truly human-centered industrial environments.

4.3 Multimodal analysis in HRC tasks

4.3.1 Background

While postural analysis captures the physical dimension of human adaptation, multimodal analysis integrates multiple signals to provide a more comprehensive picture of human performance. For instance, by synchronizing and jointly analyzing data streams such as motion capture, electromyography and eye tracking, researchers can investigate how different systems interact to support task execution. This integration allows the study of temporal correlations, causal relationships, and cross-modal compensatory strategies, revealing how posture, muscle activity, and visual attention dynamically adapt to environmental demands or collaborative interactions. Multimodal analysis thus extends beyond single-domain measures to uncover the complexity of human adaptation. In contexts such as ergonomics, rehabilitation, and human–robot collaboration, this approach is particularly valuable for developing a holistic understanding of performance and for guiding the design of adaptive human-centered systems.

Importantly, multimodal approaches are not intended to capture every aspect of human behavior, but rather to integrate complementary domains that reveal specific components of human performance. In HRC, motor behavior emerges from the interaction of multiple subsystems, including postural control, neuromuscular coordination, movement planning, and cognitive attention. Integrating different measurement modalities therefore provides a more coherent understanding of how these systems adapt to task demands. In this study, postural metrics were used to evaluate whole-body stability, EMG measures quantified neuromuscular strategies and effort, kinematic parameters characterized movement organization, and gaze metrics captured attentional and cognitive processes. Together, these domains form a structured multimodal framework for examining how collaborative and cognitively demanding environments shape human sensorimotor behavior from multiple perspectives.

Among the various methods, the assessment of the muscular activity through sEMG plays a central role [149], especially when recorded from upper limbs and trunk muscles. Indeed, these EMG signals proved to be powerful tools to estimate fatigue levels [292], [293], [294] but also ergonomic risk [295], [296] and physical effort [297], given the positive correlation between muscle activation and these factors. In particular, coactivation has emerged as a key indicator for ergonomic assessments and biomechanical risk evaluation in HRC [298], [299], [300], [301]. Increased coactivation of trunk muscles is often associated with greater trunk stiffness. While this mechanism helps protect the spine, it also results in higher compression and shear forces, thereby increasing the risk of work-related MSDs [302].

Another essential dimension in this context is provided by kinematic analysis, which offers objective and quantitative means of assessing how human movement, coordination, and performance are affected by interaction with robotic partners. Kinematic measures are fundamental for understanding motor strategies, ergonomics, and interaction quality in HRC. By studying human kinematics, researchers can find valuable insights into the mechanics of human movement, offering information pertinent to a wide array of human factors in HR, such as assessing ergonomics [295], [303], [304], determining fatigue levels [305], discerning human intention [306], [307], [308], and correlating trust [309]. For example, human operators tend to adapt their movement strategies when performing tasks with robots, often modifying their speed, trajectory, or movement smoothness to align with the cobot behavior [141], [232]. Kinematic metrics such as joint angles, velocity profiles, and trajectory smoothness enable the quantification of these adaptations, providing insights into how natural human motion patterns change during robotic interaction.

Equally important is the assessment of visual attention and cognitive processes involved in HRC tasks. To this aim, measuring gaze behavior allows researchers to understand how operators perceive, interpret, and anticipate robot actions within shared workspaces. Eye tracking is a particularly promising technique, as it provides both eye-movement and pupil-based physiological measures, offering insights into both voluntary and involuntary neural responses to stimuli [149]. Gaze-related features can be analyzed to assess awareness [310], [311], [312], trust [313], [314], mental workload [315], [316], [317], and stress [310], [318]. Visual attention plays a crucial role in ensuring safe and effective cooperation: how an operator allocates gaze between the robot, the task space, and other stimuli reflects situational awareness, trust, and task understanding [319]. Frequent gaze shifts between the robot and workspace may indicate monitoring behavior or uncertainty, while sustained attention to the robot's end-effector can suggest predictive engagement [320]. Conversely, increased gaze dispersion or longer fixations may indicate higher cognitive effort or reduced task fluency [102], [321]. Understanding these gaze patterns also supports the design of more transparent and human-aware robots, enhancing communication, motion planning, and predictability – ultimately fostering trust in HRC systems [319].

In the present study, a manual handling task was performed under unassisted execution and interaction with a cobot in the presence of external stimuli providing specific timing cues for task execution and distinct task demands. This investigation integrates multiple methodologies, including postural metrics derived from the center of pressure, muscular coactivation of upper-limb and trunk muscles, kinematic parameters, and eye-tracking metrics.

More specifically, this study is organized around two complementary lines of analysis: the first examines the impact of increased cognitive load on task execution, while the second focuses on modalities of motor inhibition following a stop signal. Multimodal behavioral responses are hypothesized to adapt to variations in cognitive demands induced by task conditions. Increased cognitive load is expected to alter postural stability and muscular coactivation, but also movement and gaze patterns, reflecting a shift in motor and cognitive control strategies during task execution. On the other hand, successful and failed responses to motor inhibition are expected to be characterized by distinct multimodal signatures, with failed inhibitions associated with greater postural adjustments, higher EMG coactivation, and altered movement and gaze behavior, reflecting reduced efficiency in inhibitory motor control. Together, these analyses provide a comprehensive view of how cognitive demand and inhibitory control influence task performance.

Investigating these conditions will help to explore how the presence of the robot and external constraints may influence muscle activation patterns, movement dynamics, and potential ergonomic risks, providing a nuanced view of human adaptation and performance in collaborative and constrained contexts.

4.3.2 Materials and methods

Participants

21 right-handed subjects (age: 26.8 ± 2.6 years; sex: 9 males; height: 171.6 ± 9 cm; weight: 68.3 ± 11.7 kg; mean ± std) participated in the experimental campaign. Participants were recruited based on their non-familiarity with the task and absence of any known musculoskeletal, neurological, or visual impairments. Prior to participation, subjects provided informed consent, and the study was approved by the institutional ethics committee. Participants were instructed to follow specific guidelines to ensure consistency in data collection and minimize variability due to external factors.

Experimental protocol

The chosen protocol involved a manual handling task in collaboration with a robotic arm (cobot), with occurrences of visual and audio stimuli, also designed to introduce disturbances to the task execution and increase cognitive load. These disturbances to the natural task execution were introduced randomly, following the stop-signal task paradigm, according to which a stop signal is presented to a subject to monitor their ability to inhibit movement [322]. This aspect is of particular interest in collaboration activities, as it helps identify the ability to cancel motor planning when the behavior of the co-worker deviates from what expected.

Participants received verbal instructions on how to perform the task. They were then asked to begin the task by placing their dominant hand on an object (a rectangular box measuring approximately 14 x 12 x 6 cm and weighing 1 kg) positioned at the center of the table in front of them. The cobot then randomly moved to the right or left side of the table. After a randomized interval of 500 to 800 ms, the LEDs positioned on the cobot's end-effector turned green for 100 ms, signaling the participants to start the task towards the side where the robot has moved to. The subsequent steps varied based on one of two different task conditions (non-stop or stop), occurring randomly, and described in the following.

In the *non-stop* condition, the participant had to scan the box and place it at an intermediate station. Consequently, the LEDs turned green for 2 seconds, during which the participants had to decide whether to request assistance from the cobot. Assistance was provided if the participant gently nudged the robot's end-effector with their hand, prompting the cobot to pick up the box and return it to its starting position. If no assistance was requested, the participants autonomously completed the task, returning the box to the starting position.

In the *stop* condition, the LEDs turned red for 100 ms, indicating that participants had to stop their action and keep the box in the central position. This condition reflected the stop-signal paradigm, which had been introduced to analyze the ability to inhibit movements. A staircase procedure adjusted the stop-signal delay (SSD) based on the participant's performance [323]. The SSD started at 100 ms (from the green LEDs signal). Correct stop trials increased the SSDs by 50 ms on the successive stop trial, while incorrect stop trials decreased it by 50 ms. The SSD ranged from 100 ms to 600 ms.

Each participant performed 100 trials, divided into 5 sessions with short breaks in between. Stop trials accounted for 30% of the total trials and were presented in random order, with the sequence varying for each participant. Trials were evenly divided between the right and the left side. Prior to the experiment, a baseline phase was performed, where participants executed the task, completing approximately 10 trials on each side. During this phase, unlike the five experimental sessions, participants performed the task without receiving any guidance from the cobot or other external stimuli, establishing a reference for their natural task execution.

Experimental setup

The experimental setup included a combination of sensors and devices designed to capture data across multiple perspectives. Postural data were captured using two force platforms, while surface EMG signals were recorded through wireless sensors (both technologies from BTS SMART-DX, BTS Bioengineering, Milan, Italy). sEMG data were recorded from sixteen muscles: right brachioradialis, right extensor carpi radialis, right biceps long head, right lateral triceps, right anterior deltoid, right medial deltoid, right posterior deltoid, right pectoralis major, upper trapezii, lower trapezii, infraspinatus, erector spinae. Gaze-related data were collected using Tobii Pro Glasses 3 (Tobii AB, Stockholm, Sweden). Finally, a reduced marker set of seven passive markers (right wrist, right elbow, right and left shoulders, neck, and right and left posterior superior iliac spines) was adopted with the BTS motion capture system (BTS SMART-DX, BTS Bioengineering, Milan, Italy). Sampling frequency was 1000 Hz for EMG data and 250 Hz for kinematic and postural data.

The experimental setup featured a workstation table with a cobot (Franka Emika Panda, Munchen, Germany) positioned opposite the subject, who is seated on a chair. The chair was positioned on the BTS force platforms, and its height was adjusted to ensure that the subject's arms form a 90° angle with the table. A schematic representation is presented in Figure 29, illustrating the placement of devices on the table, which has been carefully defined to optimize ergonomics and ensure comfortable task execution.

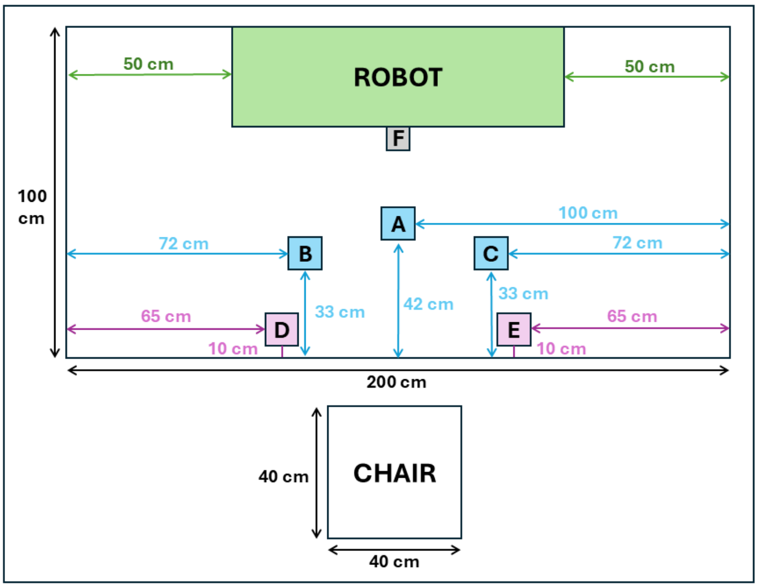

Figure 29. Schematic representation of workstation table and chair (view from above). Colors differentiate devices: green for robot, blue for conductive-ink switches (A, B, B), pink for RFID detectors (D, E), and gray for LEDs (F).

The subject sat on a chair, whose height was adjusted to ensure that the subject's arms formed a 90° angle with the table. Figure 30 illustrates a participant wearing all the sensors.

Figure 30. Image photo of one participant ready to start the experiment.

All signals were acquired simultaneously using a DAQ USB-6003 device, controlled via LabVIEW (National Instruments, Austin, TX, USA) for digital I/O:

- The DAQ inputs, configured in pull-up mode, connect to three conductive-ink switches, two RFID detectors, and two end-switches. The conductive-ink switches, positioned on the table (locations

A, B, and C in Figure 29), drive three corresponding digital inputs on the DAQ to detect the presence of an object. The RFID-RC522 modules, positioned on the table (locations D and E in Figure 29) and controlled by Arduino Nano boards (ARDUINO LCC, Turin, Italy), detect a RFID tag fixed beneath the object. Upon detection, a buzzer activates to simulate a cashier scanning procedure. The end-switches are fixed on the robot's main joint, to determine its rotation to the right or left side, generating a digital input for the DAQ to detect maximum joint excursions.

- Multicolor LEDs (green and red) are mounted on the robot's end-effector facing the participant and are driven by DAQ digital outputs. Their on/off switching provides instructions to the participants according to the experimental protocol. To synchronize all devices, a trigger signal generated by the Tobii system is acquired by LabVIEW through the DAQ and forwarded to the BTS system.

Relevant time parameters were acquired through LabVIEW synchronously with gaze data (through the Tobii system), and kinematic, EMG and postural data (via the BTS system). The *session start time* corresponds to the instant at which the system starts recording. Additionally, the following times are defined: *start time* when the robotic arm arrives at its right/left position, *go time* when the LEDs turn on green, *stop time* when LEDs turn red, *pick time* when the object is lifted, *scan time* when the object is scanned, *decision time* when the object is placed at the lateral station, *end time* when the object is placed back to its initial position.

A dedicated system architecture was developed to execute the experimental protocol. Figure 31 illustrates the detailed workflow, highlighting the interconnections among sensors, devices, and processes involved. At the start of each session, the system began recording data. When the robot's end-switch was activated – indicating a turn to the right or left – the current trial started, and the LEDs turned green. Two possible conditions could then occur:

- In the *stop* condition, the LEDs turned red, and the central switch detected whether the participant had picked up the box. If the box had been lifted, the system recorded the precise time of the action, allowing detection of hand movement and its timing to trigger and characterize an error stop condition.
- In the *non-stop* condition, the central switch recorded the exact time at which the participant had picked up the box, while the RFID system detected the scanning action, provided auditory feedback, and logged the corresponding timestamp. Once the box was placed in the lateral position, conductive-ink switches activated the green LEDs to indicate the end of this phase. At this stage, if the participant requested assistance, the robot would complete the task.

Finally, the central switch signaled the end of the current trial, and the process was repeated across multiple trials.

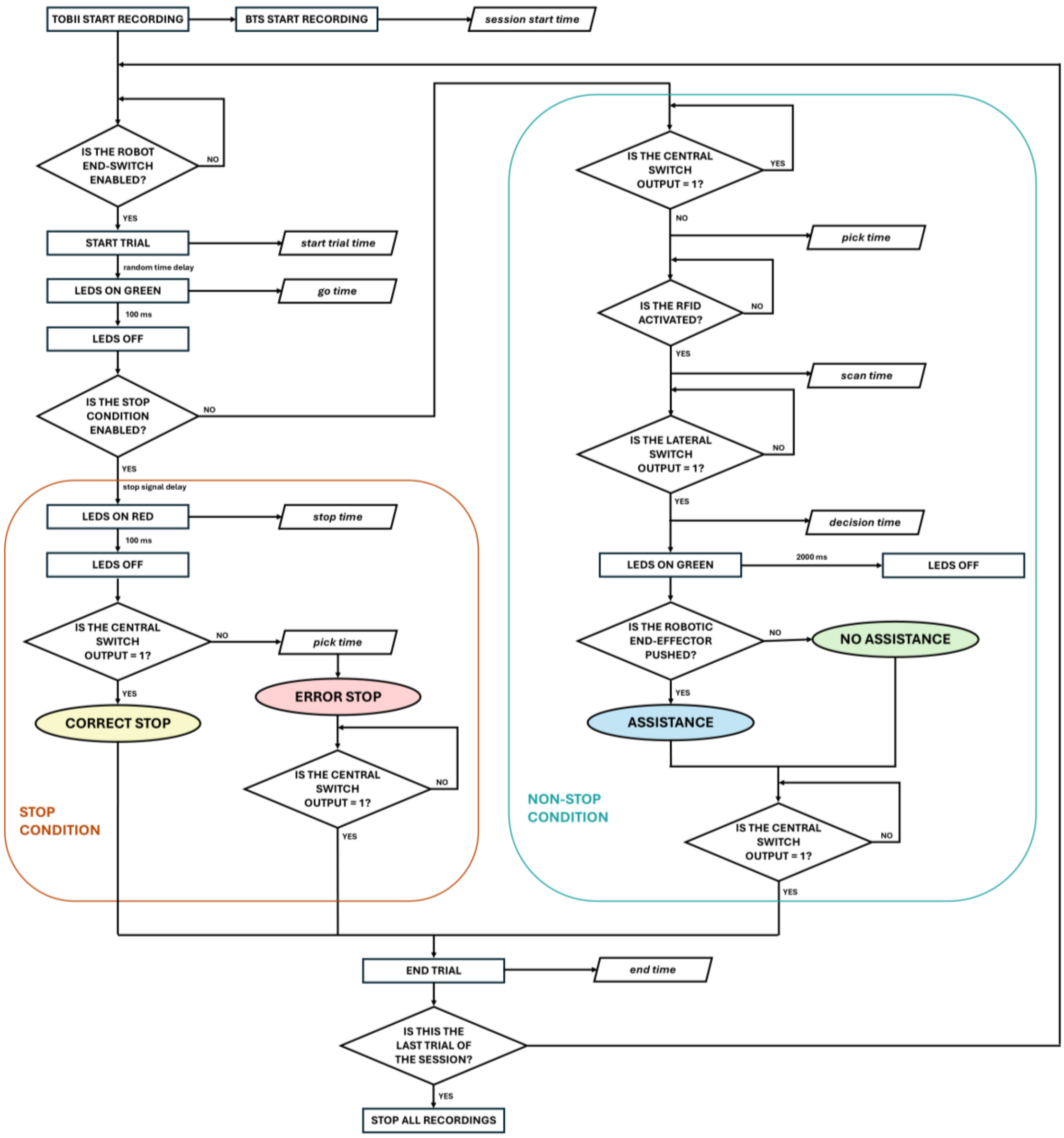

Figure 31. Workflow of the experimental setup. Rectangles represent actions, rhombuses denote questions, parallelograms indicate saved time variables, and ellipses specify the four trial conditions.

Data analysis

COP, kinematic and EMG data from baseline and experimental trials were selected and analyzed in MATLAB (MathWorks, Natick, MA). The collected data corresponded to entire experimental blocks. For the experimental trials, segmentation was performed by extracting the data between the corresponding *start* and *end* timestamps recorded via Labview VI, ensuring analyses could be conducted on a trial-by-trial basis. Since *start* and *end* time of each trial were not available for the baseline, this segmentation was implemented using a threshold of the ML coordinate of the marker positioned on the wrist: data points exceeding or falling below this predefined spatial threshold were used to identify trial boundaries, enabling consistent extraction of individual baseline trials for subsequent analysis.

Once segmented, experimental trials were further classified into five types based on the subject's movement behavior: non-stop trial without cobot assistance (1), non-stop trial with cobot assistance (2), stop trial without picking the object (3), stop trial with object picking (4), and stop trial with object picking and further movements (5). The distinction between *stop* and *non-stop* trials was based on whether the *stop time* was recorded: trials in which the *stop time* was NaN were classified as *non-stop* trials. To determine whether subjects requested cobot assistance, a threshold on the vertical coordinate of the wrist marker was applied: when the wrist vertical position exceeded 50 cm, the trial was labeled as a cobot assistance request (type 2), as participants reached this level only to touch the high-positioned end-effector to ask for help. These trials (type 2) also underwent further segmentation, from *start time* to *rest time*, defined as the moment when the subject returned to the resting position and specifically identified using a threshold on the vertical coordinate of the wrist marker. For *stop* trials, classification was based on the *pick time* and subsequent movement. Trials in which the pick time was NaN were classified as type 3, indicating that the subject did not lift the object. If a valid *pick* time was recorded, the trial was further classified as type 4 or type 5. Type 4 trials corresponded to cases where the ML coordinate of the wrist marker did not exceed 2 cm, indicating that the subject picked the object without initiating substantial movement. Type 5 trials occurred when the ML wrist coordinate exceeded 2 cm, indicating that the subject not only picked the object but also started the actual movement, representing a larger deviation compared to type 4 trials. All these steps are schematically described in Figure 32. For clarity, the experimental trials will henceforth be labeled TT1 to TT5, with the baseline trials correspondingly labeled TT0.

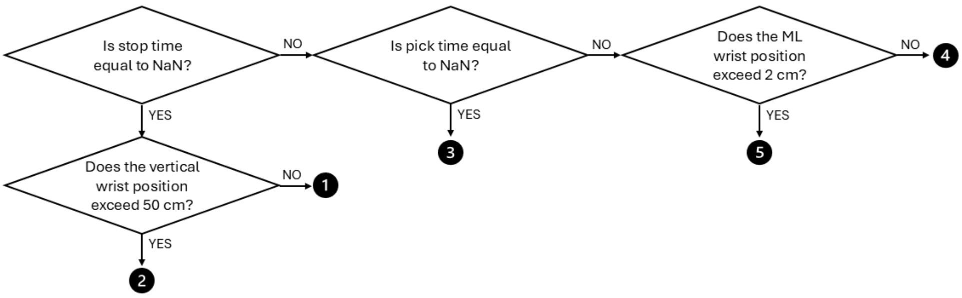

Figure 32. Flowchart illustrating the logic for classifying experimental trials into five types.

Postural analysis

The postural analysis of COP data followed the same methodology for COP-derived parameters detailed in *Section 4.2.2*, with adaptations specific to the present dataset. Mean values of the selected parameters were then computed and subjected to inferential statistical analysis to assess potential differences across conditions.

Kinematic analysis

Kinematic data were analyzed to investigate participants' motor performance during the task, focusing on movement execution, smoothness and joint kinematics. All kinematic signals were filtered using a low-pass Butterworth filter (cutoff frequency of 5 Hz and order 3) to remove high-frequency noise. Kinematic trajectories were then first differentiated to obtain velocity, acceleration, and jerk profiles, allowing a detailed characterization of movement dynamics. Before any differentiation procedure, the signals were further filtered to minimize noise amplification due to the derivative computation.

Movement smoothness was assessed using two indices – the Log Dimensionless Jerk (LDLJ) and the Spectral Arc Length (SAL) – both computed from the wrist trajectory. These two metrics have been chosen among the large variety of smoothness metrics because they have gained widespread recognition for their reliability and robustness in quantifying smoothness [324], [325], [326]:

- LDLJ is a time-domain metric that quantifies smoothness based on the normalized jerk (the third derivative of position). It provides a dimensionless measure independent of movement duration and amplitude, with lower values indicating smoother movements. Together with the dimensionless jerk (DLJ), the LDLJ is the only valid jerk-based measure of movement smoothness [203]. Unlike DLJ, LDLJ addresses the physiological range through the natural log function [327]. It is calculated as in [327]:

$$LDLJ \triangleq -\ln|DLJ|\,; \qquad DLJ \triangleq -\frac{(t_2 - t_1)^5}{{v_{peak}}^2} \int_{t_1}^{t_2} \left|\frac{d^2 v(t)}{dt^2}\right|^2 dt$$

  where $v(t)$ is the movement speed, t is time, t_1 and t_2 are the start and end times of the movement, and v_{peak} is the peak speed.

- SAL is a frequency-domain measure that evaluates the smoothness of a trajectory based on the shape of the arc length of the Fourier magnitude spectrum of the velocity profile [203]. It quantifies how concentrated or spread the movement's spectral content is, with more negative SAL values reflecting reduced smoothness. It is calculated as in [327]:

$$SAL \triangleq -\int_0^{\omega_c} \sqrt[2]{\left[\left(\frac{1}{\omega_c}\right)^2 + \left(\frac{d\hat{V}(\omega)}{d\omega}\right)^2\right]}\, d\omega; \qquad \hat{V}(\omega) = \frac{V(\omega)}{V(0)}$$

  where $V(\omega)$ is the Fourier magnitude spectrum of $v(t)$, $\hat{V}(\omega)$ is the normalized magnitude spectrum – normalized with respect to the DC magnitude $V(0)$, and ω_c is fixed to be 40π (corresponding to 20 Hz).

Joint kinematics were analyzed to quantify the range of motion (ROM) of the upper limb and trunk during task execution, through the computation of five specific angles, as illustrated in Figure 33. Elbow flexion/extension was computed as the 3D angle between the upper arm vector (defined by the line connecting the shoulder and elbow markers, oriented from shoulder to elbow) and the forearm unit vector (connecting the elbow and wrist markers, oriented from elbow to wrist). Shoulder elevation was evaluated in two planes, as the 2D angles between the projections of the upper arm vector and the vertical axis on the frontal plane (for shoulder ab/adduction) and on the sagittal plane (for shoulder flexion/extension). Horizontal shoulder abduction/adduction was calculated in the transverse plane as the 2D angle between the projected upper arm vector and the AP axis. Trunk flexion/extension was computed from the sagittal-plane projection of the vector joining the neck and mid-PSIS markers relative to the vertical axis.

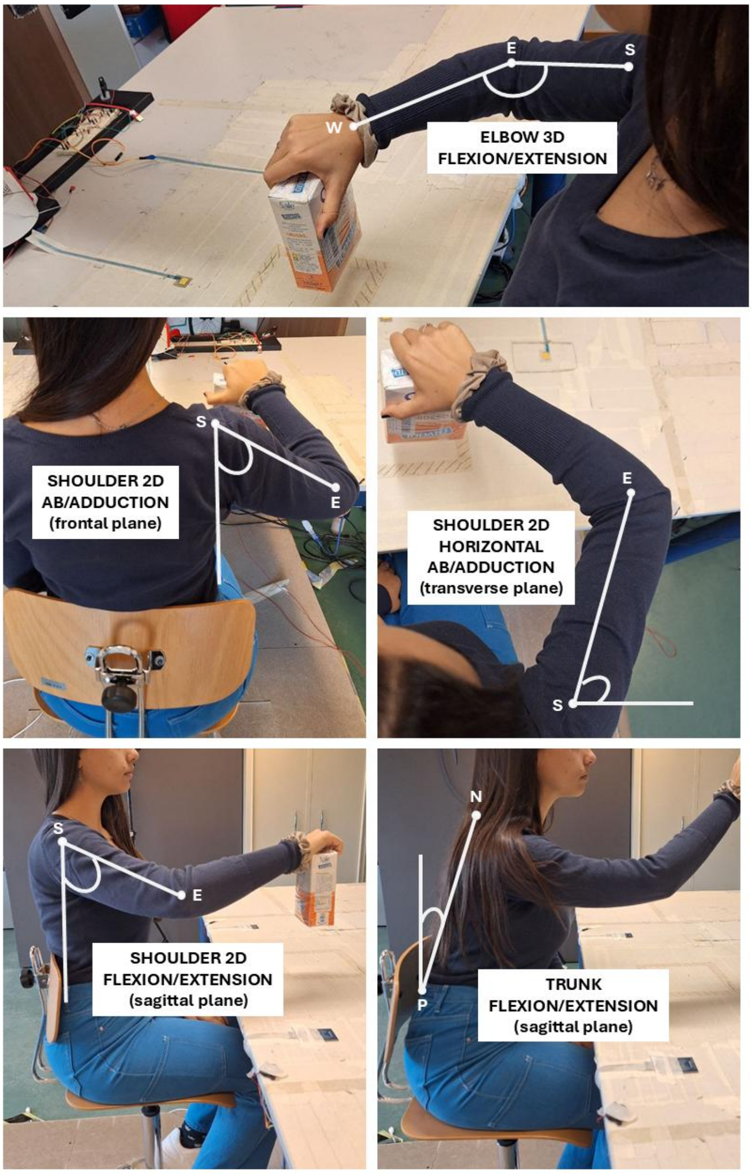

Figure 33. Illustration of the five considered articular angles.

All 2D angles were computed using the *arctangent* function, which allows preserving the sign of rotation – an important feature for distinguishing movement direction – unlike the 3D *arccosine* computation used for the elbow angle, using the same approach described in [328]. For each angle and trial, the ROM was determined as the difference between the maximum and minimum values of the corresponding angle within the segmented movement. Mean ROM values across trials were then calculated for each subject and experimental condition and subsequently used for inferential statistical analyses to assess potential differences between conditions.

Muscular analysis

EMG signals were band-pass filtered (5th order, 20-400 Hz) to remove noise and artifacts, and ECG interference was removed. This filtered signal was then rectified and low-pass filtered (5th order, cutoff frequency 5 Hz) to obtain the amplitude and then normalized to the maximum value across all trials. The Time-Varying Multi-Muscle Coactivation function (TMCf) [329] was computed to estimate the coactivation of different sets of muscles. TMCf makes it possible to capture a group-level amount of coactivation, when the number of involved muscles is higher than two. The mean values of the coactivation functions within the trials were calculated as coactivation indices, providing an overview of the overall task execution [298].

The analysis focused on four muscle groups, categorized according to their functional roles: distal upper limb (i.e., brachioradialis, extensor carpi radialis, biceps long head, and lateral triceps), proximal upper limb (i.e., anterior deltoid, medial deltoid, posterior deltoid, and right pectoralis major), scapular stabilizers (i.e., upper trapezii and infraspinatus) and postural stabilizers (i.e., lower trapezii and erector spinae).

Oculomotor analysis

For each timestamp, gaze data provided the classification of eye movement type (i.e., fixation, saccade, or other). Using this information, periods of fixations and saccades were isolated for each trial. Number and rate of fixations and saccades were then calculated as primary metrics of visual behavior. Subsequently, for each subject, these metrics were averaged across all trials of the same type, providing subject-specific mean values for each experimental condition. It should be noted that gaze data were not collected during the baseline condition, as this condition was intended to be as minimally demanding as possible, allowing participants to perform the task in a purely naturalistic setting.

Statistical analysis

Normality of the analyzed parameters was assessed using the Shapiro-Wilk test. Since at least one of the distributions of each parameter was not normal, non-parametric statistical analyses were applied. To evaluate differences across the different experimental conditions, a Friedman test was performed. When a significant main effect was found, pairwise comparisons were conducted using the Wilcoxon Signed-Rank Test with Bonferroni correction. The significance level was set to 0.05, 0.01 and 0.001 (*, ** and ***, respectively).

4.3.3 Results

This chapter is organized around two complementary lines of analysis. The first examines the impact of increased cognitive load on task execution, comparing performance across TT0, TT1, and TT2 (although gaze data were not available for TT0). The second focuses on motor inhibition following a stop signal, considering performance exclusively in TT3, TT4, and TT5. Together, these analyses provide a comprehensive view of how cognitive demand and inhibitory control influence task performance.

Cognitive load effect

Figure 34 presents results from four traditional COP-derived sway parameters. All parameters were lowest in TT0 (MDIST: $p < 0.01$ for TT0–TT1 and TT0–TT2; MVEL: $p < 0.001$ for TT0–TT1 and TT0–TT2; CE-AREA: $p < 0.01$ for TT0–TT1 and $p < 0.001$ for TT0–TT2; SW-AREA: $p < 0.001$ for TT0–TT1 and TT0–TT2), whereas no significant differences were observed between the guided conditions (TT1 vs TT2).

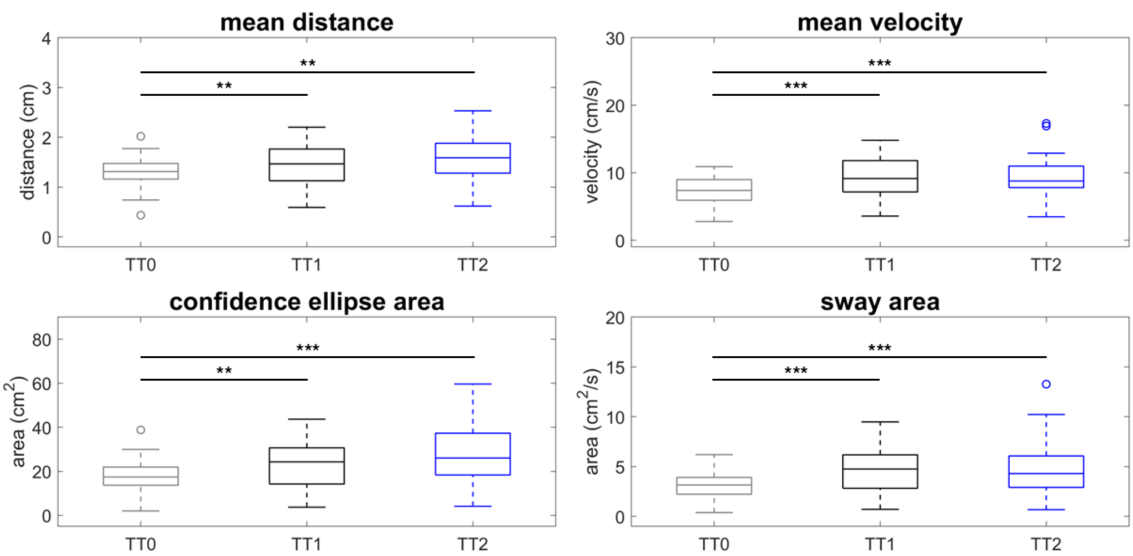

Figure 34. Distribution of COP-derived sway parameters, differentiated by task conditions.

Muscle coactivation results are shown in Figure 35. Coactivation progressively decreased across conditions (TT0 > TT1 > TT2). In the upper limb, all conditions differed, albeit with varying levels of significance ($p < 0.01$ for TT0–TT1 in distal upper limb and TT1–TT2 in proximal upper limb; $p < 0.001$ in all other comparisons). For the trunk, scapular stabilizers did not differ across conditions, while postural stabilizers showed significant differences between TT0 and TT2 ($p < 0.01$) and between TT1 and TT2 ($p < 0.001$).

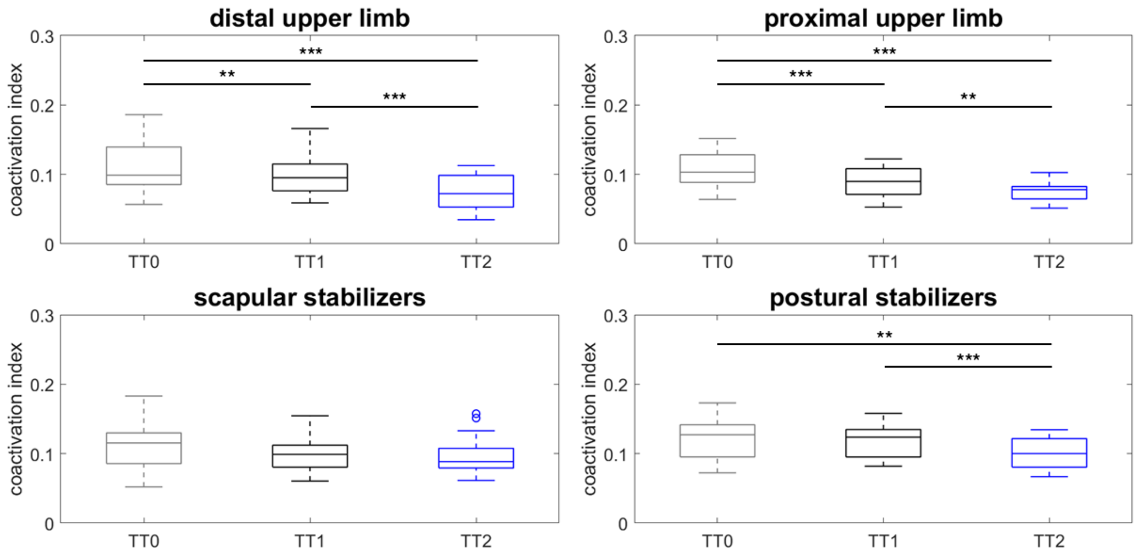

Figure 35. Distribution of coactivation index values, differentiated by task conditions.

Figure 36 reports the smoothness of end-effector kinematics. Both smoothness metrics were similar between TT0 and TT1 but significantly lower in TT2 ($p < 0.001$).

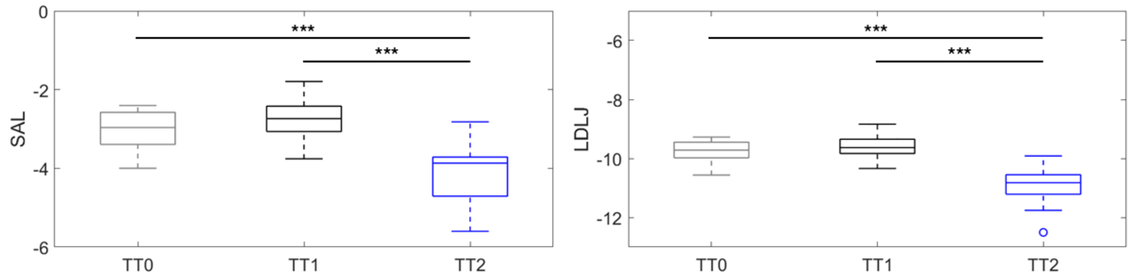

Figure 36. Distribution of smoothness SAL and LDLJ values, differentiated by task conditions.

Joint kinematics are illustrated in Figure 37, showing ROM distributions for each angle across task conditions. ROM values were similar in TT0 and TT1 but substantially increased in TT2 ($p < 0.001$ for all angles).

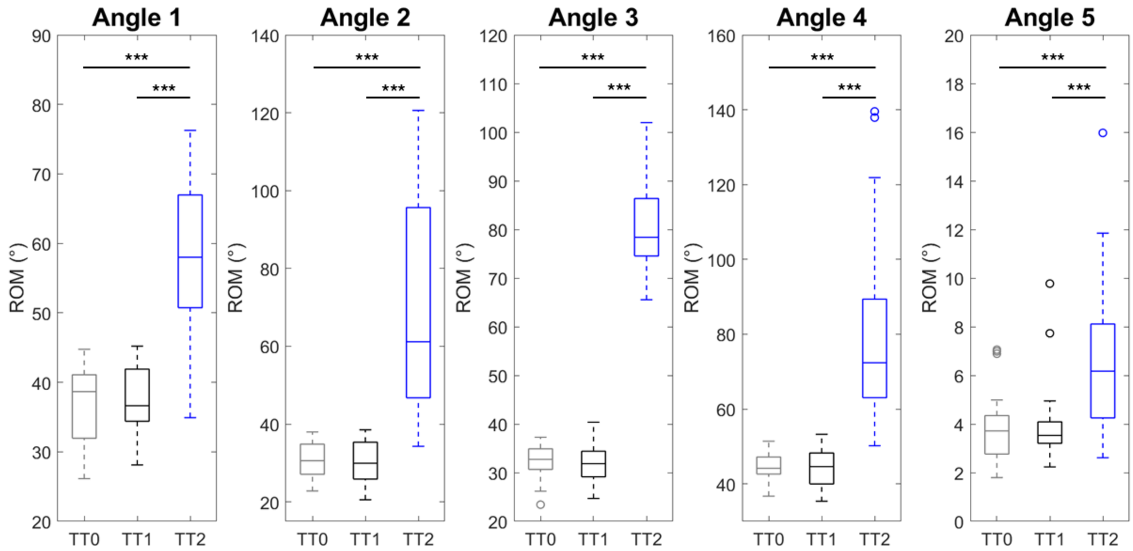

Figure 37. Distribution of ROM values of 5 different angles (elbow flexion/extension, shoulder ab/adduction on the frontal plane, shoulder flexion/extension on the sagittal plane, shoulder horizontal ab/adduction on the transverse plane, and trunk flexion/extension on the sagittal plane, respectively), differentiated by task conditions.

Finally, Figure 38 presents oculomotor results in terms of fixation and saccade numbers and rates. All metrics were higher in TT2 compared to TT1 ($p < 0.001$).

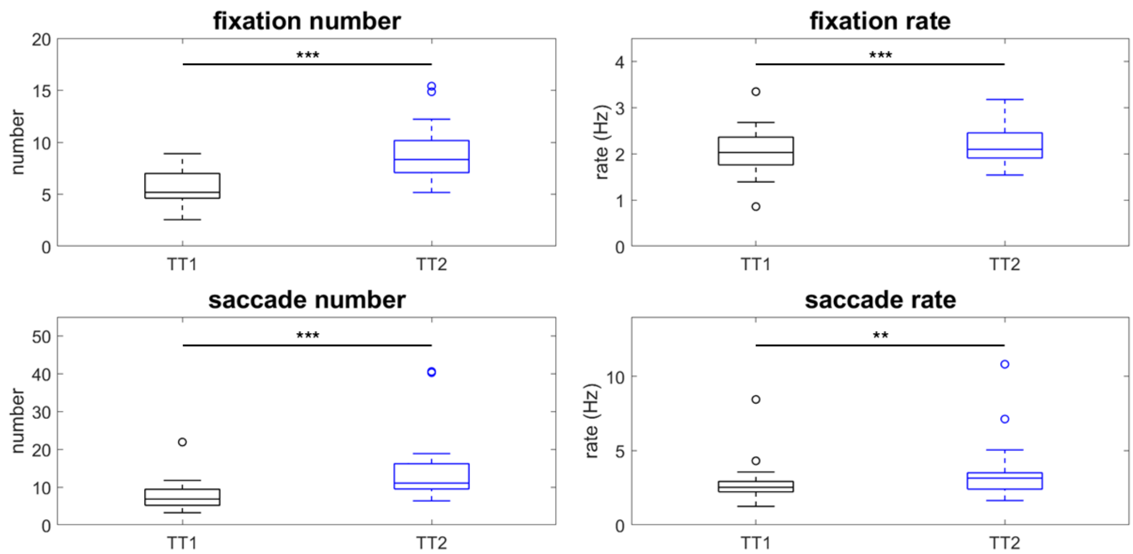

Figure 38. Distribution of oculomotor features, differentiated by task conditions.

Motor inhibition

Figure 39 shows COP-derived sway parameters during motor inhibition trials. All parameters increased progressively from TT3 to TT4 and then TT5 ($p < 0.001$ for all comparisons).

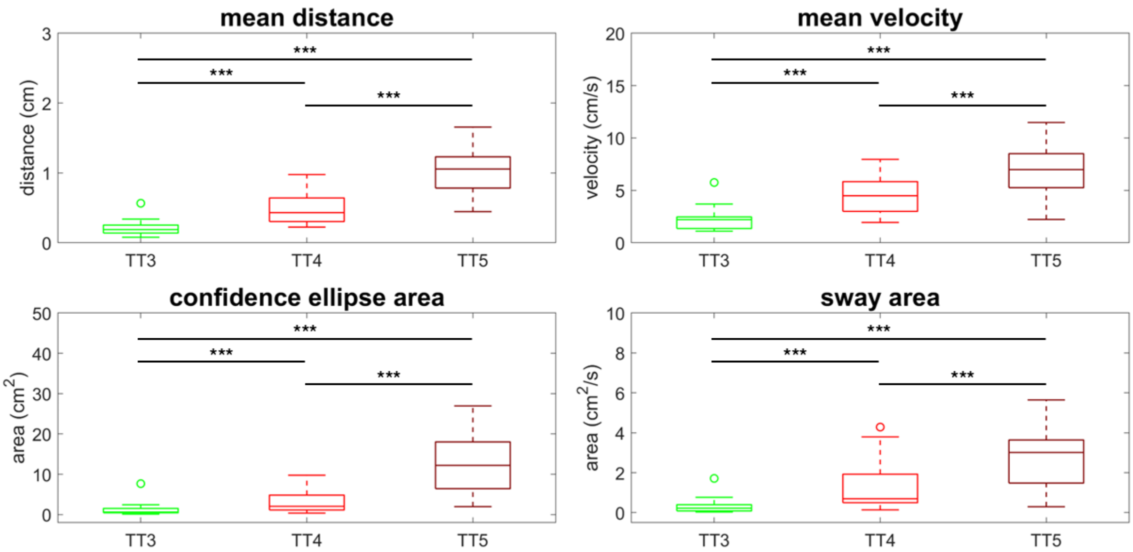

Figure 39. Distribution of COP-derived sway parameters, differentiated by task conditions.

Muscle coactivation results are reported in Figure 40. TT5 consistently exhibited the highest coactivation across all muscle sets ($p < 0.001$). TT4 differed from TT3 only in upper-limb muscles ($p < 0.01$), whereas trunk coactivation was comparable between the two conditions.

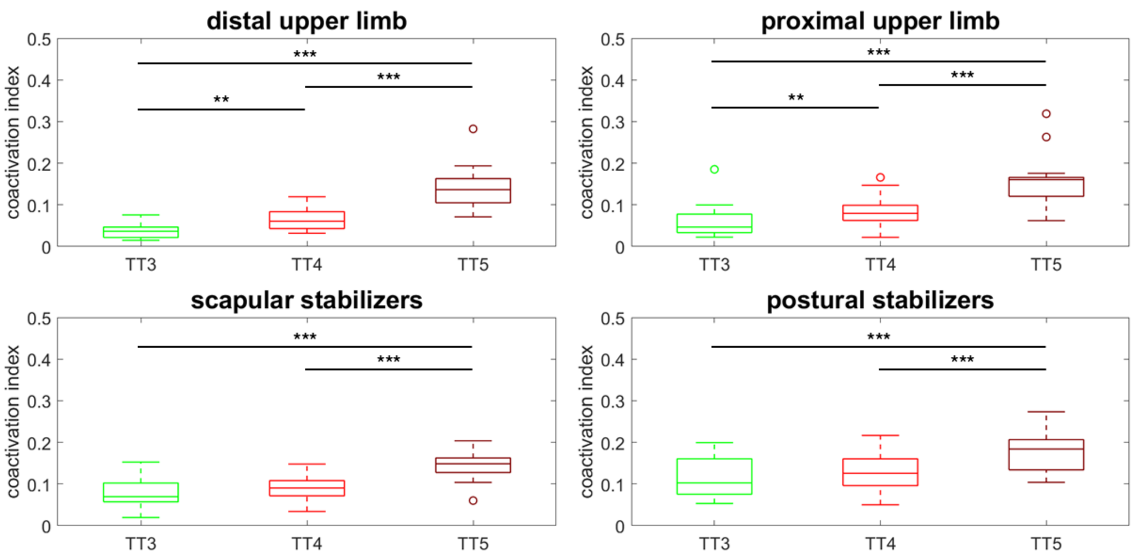

Figure 40. Distribution of muscle coactivation indexes, differentiated by task conditions.

End-effector smoothness is illustrated in Figure 41. Significant differences were observed across task conditions, with an overall trend of increasing smoothness from TT4 to TT5 and then to TT3, although significance levels varied ($p < 0.001$ for SAL in TT3-TT5 and LDLJ in TT3-TT4 and TT3-TT5; $p < 0.01$ for SAL in TT3-TT4; $p < 0.05$ for LDLJ in TT4-TT5).

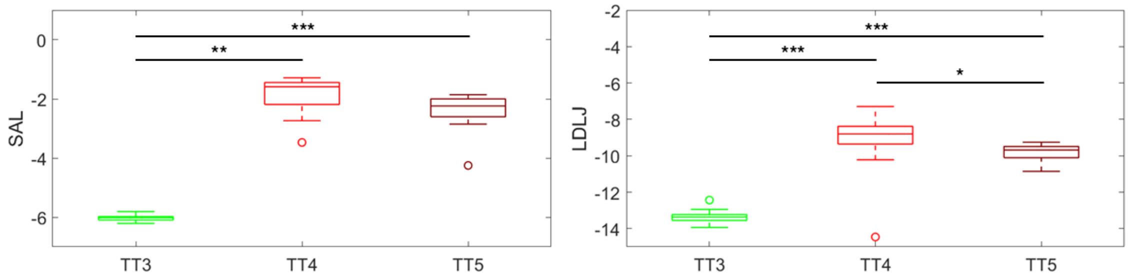

Figure 41. Distribution of muscle coactivation indexes, differentiated by task conditions..

Joint kinematics are presented in Figure 42, showing ROM distributions for each angle. ROM was comparable between TT3 and TT4 but increased substantially and significantly in TT5 ($p < 0.001$ for all angles).

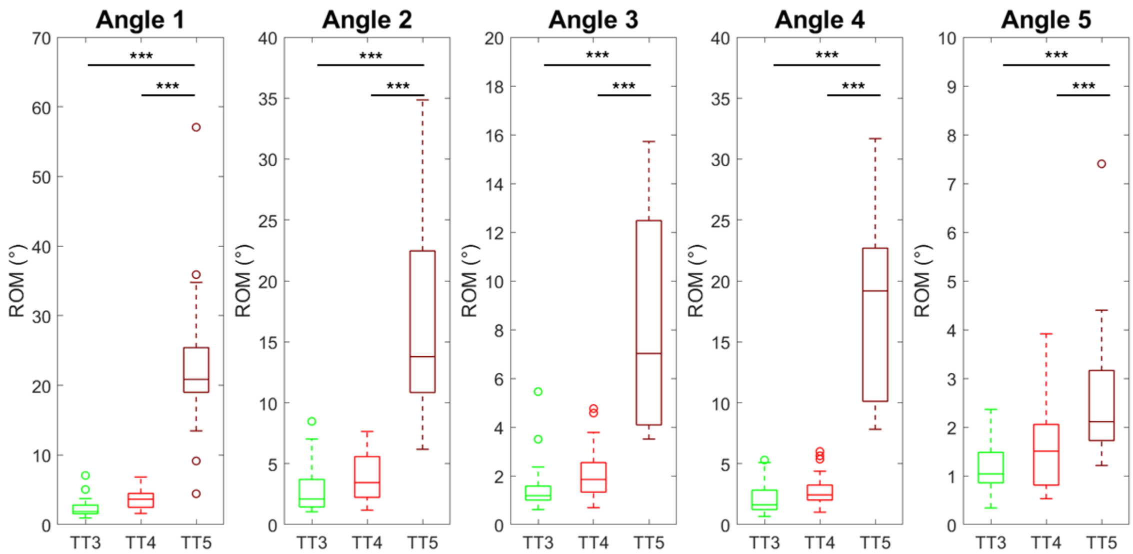

Figure 42. Distribution of ROM values of 5 different angles (elbow flexion/extension, shoulder ab/adduction on the frontal plane, shoulder flexion/extension on the sagittal plane, shoulder horizontal ab/adduction on the transverse plane, and trunk flexion/extension on the sagittal plane, respectively), differentiated by task conditions.

Finally, oculomotor results are presented in Figure 43 as the number and rate of fixations and saccades. Although fixation and saccade numbers were highest in TT3 ($p < 0.001$), these differences disappeared when considering rates, which were comparable across all conditions for both types of eye movements.

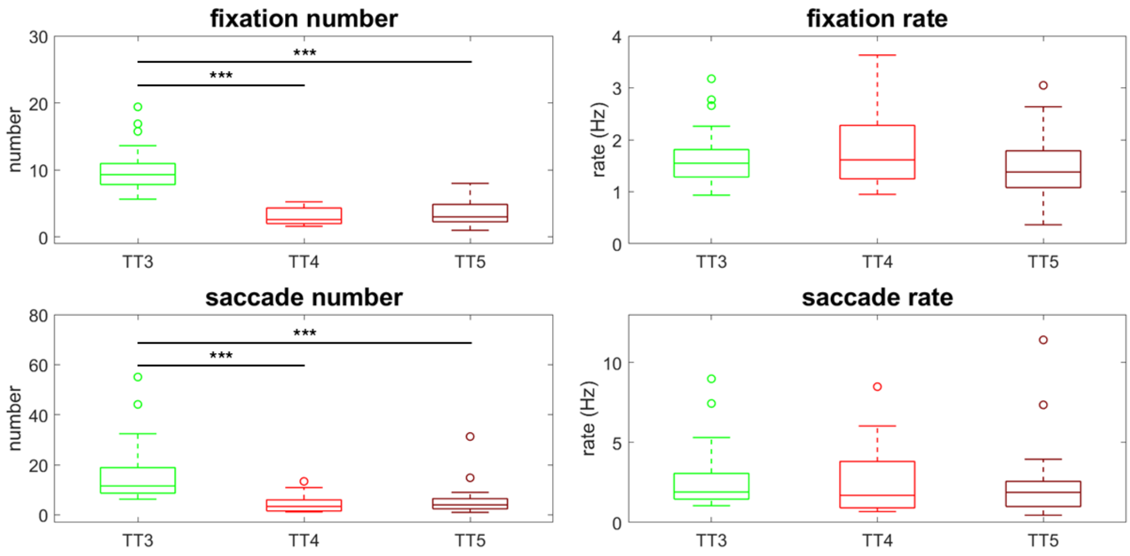

Figure 43. Distribution of oculomotor features, differentiated by task conditions.

4.3.4 Discussion

The present discussion integrates postural, kinematic, muscular, and oculomotor findings to clarify how human behavior adapts to high cognitive load and motor inhibition, providing a multidimensional account of how control modes, external assistance, and inhibitory constraints shape motor behavior.

Cognitive load effect

Results provide converging evidence that external guidance fundamentally alters human motor and cognitive behavior, even when physical task demands are partially offloaded to a robotic agent. Across postural, muscular, kinematic, and gaze-related measures, a consistent pattern emerges in which cognitive guidance – rather than the degree of physical task execution – primarily shapes human behavior. This perspective aligns with dual-task frameworks in which cognitive demands compete with motor control resources, influencing performance across multiple domains (e.g., posture, attention, motor planning) [330].

Postural analysis showed the lowest sway during autonomous task execution (TT0), whereas both guided conditions (TT1 and TT2) exhibited significantly higher values, with no differences between them. This suggests that external visual–cognitive guidance, rather than whether the task is fully or partially executed by the human, is the primary factor affecting postural control. The finding aligns with evidence that increased attentional demands can impair balance regulation, as dual-task cognitive load competes for limited shared resources [331], [332]. The absence of differences between TT1 and TT2 further indicates that postural control is sensitive to guidance per se, but relatively insensitive to the extent of physical involvement once attentional demands are elevated.

At first glance, the reduced sway in TT0 might be merely interpreted as reflecting greater postural stability. However, integrating these results with the EMG findings modifies this interpretation. Muscular coactivation progressively decreased from TT0 to TT2, indicating that participants relied more heavily on coactivation in TT0. This high coactivation likely reflects a conservative, rigidity-based stabilization strategy driven by internal control [333], rather than more efficient neuromuscular regulation. In contrast, the reduction in coactivation observed with external guidance may indicate a shift toward a more efficient and adaptive neuromuscular strategy [334]. In TT2, robotic support further offloaded task execution, lowering the need for stabilizing coactivation and resulting in the lowest values.

Movement smoothness analysis further highlights differences between task conditions. The preservation of smoothness in TT1 relative to TT0 suggests that external guidance does not necessarily disrupt motor planning or execution when the human remains fully responsible for completing the task. In contrast, the reduced smoothness observed in TT2 may reflect uncertainty in motor planning, intermittent control strategies, or anticipatory adjustments related to the potential transfer of task execution to the robot. Rather than reflecting degraded motor skill, this reduction in smoothness likely captures a reorganization of movement execution under increased cognitive demands and altered task structure. This aligns with broader motor control research showing that cognitive load and task complexity can alter the temporal structure and continuity of movements, reflecting changes in planning, segmentation, and execution strategies [335]. Such discontinuities may reflect a supervisory mode of control, characterized by intermittent corrections rather than continuous predictive planning.

Joint ROMs were the highest in TT2, but this increase is likely attributable to task-specific and contextual demands rather than to changes in motor control quality. For this reason, ROM differences should be interpreted with caution, as they may primarily reflect mechanical and contextual constraints of the task rather than differences in motor efficiency, coordination, or control strategies. This limitation underscores the importance of distinguishing biomechanical constraints from neuromotor adaptations when interpreting kinematic variables.

Finally, gaze-related measures indicate that TT2 imposed the highest cognitive demands [336]. The increased number and rate of fixations suggest greater visual monitoring and information gathering, indicating heightened attentional engagement. At the same time, the increased number and rate of saccades indicate more frequent reallocation of visual attention, possibly reflecting visual search behavior, decision-making demands, and the need to monitor both task-related elements and the robotic agent. Rather than being contradictory, the coexistence of more fixations and more saccades reflects a more demanding and dynamic visual strategy, requiring both sustained attention and frequent updating of visual information. Importantly, because robotic intervention was initiated voluntarily by the participant, this oculomotor behavior likely reflects ongoing evaluation of task progression and self-monitoring processes related to deciding whether to request assistance. Moreover, the observed gaze pattern may be indicative not only of increased task monitoring, but also of higher cognitive effort or emerging mental fatigue, potentially biasing participants toward the use of robotic assistance as a compensatory strategy. Such fatigue-driven changes may have implications for long-duration HRC scenarios, where automation could inadvertently increase cognitive load. An additional aspect to consider is the potential influence of limited familiarity with the robotic system: early stages of interaction with a robotic partner may require greater monitoring and decision-making, potentially contributing to the increased cognitive and attentional demands observed [337]. While the persistence of these patterns across guided conditions suggests that they are only linked to the collaborative context itself, future studies incorporating extended familiarization phases or longitudinal designs would be valuable to disentangle novelty effects from the intrinsic cognitive demands of HRC.

A schematic overview of the multimodal findings is provided in Table 1. Taken together, these findings suggest that robotic assistance does not simply reduce human involvement but instead introduces additional cognitive and attentional demands that reshape sensorimotor behavior across multiple domains. While robotic intervention may reduce physical and muscular demands, it simultaneously increases perceptual–cognitive load and influences motor planning and coordination. This indicates redistribution rather than removal of task demands, shifting load from motor execution toward decision-making, prediction, and supervisory attention. Overall, the results support the view that HRC represents a qualitatively distinct control context [338], characterized by altered movement organization and increased cognitive engagement, rather than a straightforward intermediate condition between full autonomy and guided execution.

Table 1. Summary of multimodal findings in TT0, TT1, and TT2.

Modality	Results	Interpretation
Postural sway	Lowest in TT0 and no difference in TT1-TT2	Postural control is primarily influenced by guidance, rather than by the amount of physical task execution
Muscle coactivation	Progressive decrease from TT0 to TT1 to TT2	Increasing external support shifts muscular control from internal stabilization to adaptive efficiency
Movement smoothness	Lowest in TT2 and no difference in TT0-TT1	Guidance does not impair motor execution, but shared human–robot execution introduces different strategies
Joint range of motion	Highest in TT2 and no difference in TT0-TT1	This likely reflects task mechanics and contextual constraints, rather than motor control efficiency
Gaze behavior	Highest counts and rates in TT2	Robotic assistance requires greater attentional engagement and visual monitoring

Motor inhibition

The three task conditions considered in this context revealed a coherent pattern consistent with increasing motor engagement and decreasing inhibitory success from TT3 to TT5. Thus, the reduction in inhibitory success from TT3 to TT5 may reflect a continuum of inhibitory engagement, where insufficient suppression of motor plans leads to increased motor output and the need for supplementary motor and cognitive resources.

First, postural control exhibited a clear trend: sway amplitude was the lowest when participants successfully inhibited movement (TT3), and progressively increased when inhibition failed, particularly in the large-movement condition (TT5). This pattern suggests that unsuccessful inhibitions may recruit more extensive postural adjustments, reflecting increased whole-body involvement during unintended movement execution.

Similarly, muscle coactivation increased when inhibition failed. TT5 consistently elicited the highest levels across all muscle sets, confirming a substantial muscular engagement during larger erroneous responses. Interestingly, TT4 showed higher coactivation than TT3 only in upper-limb muscles, while trunk muscle coactivation was comparable between conditions. This dissociation may indicate that smaller incorrect responses (TT4) rely primarily on arm and shoulder muscles adjustments without necessitating broader stabilizing strategies involving trunk musculature. In contrast, larger erroneous responses (TT5) may exceed the capacity of upper-limb adjustments alone, triggering a global coactivation strategy that includes all muscle groups. Notably, coactivation levels in TT5 were even higher than those observed during task execution in TT0, TT1, and TT2, suggesting that the neuromuscular effort involved in aborting an initiated movement exceeds that required to execute the task itself. This highlights that suppressing an ongoing action – especially once substantial movement has begun – imposes a higher demand on the motor system than full movement execution.

Conversely, wrist smoothness did not follow the same trend. TT3 was quantified as the least smooth condition, but visual inspection and contextual interpretation indicate that this is likely to reflect measurement noise rather than meaningful movement. Once movement occurred, TT4 displayed the smoothest trajectories, potentially indicating relatively rapid but controlled execution of erroneously released prepotent responses. In contrast, larger erroneous movements in TT5 appeared more abrupt or less coordinated, possibly reflecting stronger action impulses or less refined motor planning under higher inhibitory failure. This distinction suggests that small erroneous movements may reflect controlled, anticipatory release processes, whereas larger errors emerge from more automatic or stimulus-driven action impulses, which are less conducive to smooth trajectory generation.

Regarding joint ranges of motion, TT5 expectedly showed the largest excursions. However, these differences appear driven primarily by task structure rather than neuromotor control strategies, emphasizing that ROM may not directly reflect cognitive or inhibitory performance. This underscores again the importance of careful selection of kinematic metrics when studying action suppression.

Finally, gaze metrics suggest that oculomotor activity might have been influenced by task duration. TT3 was associated with a larger number of fixations and saccades, yet their rates were comparable across all conditions. This may indicate that elevated counts in TT3 may reflect longer time spent maintaining inhibitory control rather than differences in visual strategy.

A schematic overview of the multimodal findings is provided in Table 2. Taken together, they converge toward a coherent interpretation of motor inhibition. Successful inhibition is associated with reduced postural sway and lower muscular co-activation, reflecting efficient neuromotor control with minimal compensatory engagement. In contrast, failed inhibition elicits progressively larger neuromotor and postural responses, with the magnitude and distribution of these responses scaling with the amplitude of erroneous movements. At the same time, the interpretive value of some metrics depends critically on measurement reliability and task structure. For instance, apparent reductions in smoothness may reflect baseline noise rather than meaningful neuromotor differences, ROM differences primarily mirror the imposed movement amplitude rather than inhibition success, and elevated fixation or saccade counts may arise from longer trial durations rather than altered visual strategies. These observations underscore the importance of multimodal integration, rate- or duration-normalization, and task-sensitive metric selection in motor inhibition research, as physiological and behavioral responses may reflect a combination of control failures and task-structural demands rather than inhibition per se.

Table 2. Summary of multimodal findings in TT3, TT4, and TT5.

Modality	Results	Interpretation
Postural sway	Progressive increase from TT3 to TT4 to TT5	Erroneous movements recruit higher postural adjustments, scaled to the magnitude of the error
Muscle coactivation	Progressive increase from TT3 to TT4 to TT5	Erroneous movements trigger increased muscular stabilization strategies, scaled to error magnitude
Movement smoothness	Progressive increase from TT3 to TT5 to TT4	Erroneous responses are more controlled with small errors and more impulsive with larger errors
Joint range of motion	Highest in TT5 and no differences in TT3-TT4	This likely reflects task mechanics and contextual constraints, rather than motor control efficiency
Gaze behavior	Highest counts in TT3 but similar rates	This likely reflects longer trial duration in correct motor inhibition, rather than changes in visual strategy

4.3.5 Conclusions

Consistent with the overarching aims of this thesis, the present study provides insights into how innovative and collaborative environments can influence human motor behavior. By combining multimodal measurements – including postural, muscular, kinematic, and gaze data – within HRC scenarios, the experiment captures not only the magnitude of behavioral and motor changes, but also their changes from the cognitive point of view. The novelty of this study lies in the integration of heterogeneous physiological and behavioral domains within a single experimental framework, enabling a system-level investigation of human adaptation in collaborative contexts. The findings demonstrate that robotic assistance with cognitive guidance reshapes motor planning, coordination, and attentional strategies, rather than simply reducing physical effort. Importantly, these results support a reinterpretation of HRC effects: collaboration should not be viewed solely as task facilitation or workload redistribution, but as a dynamical motor–cognitive coupling process reflected in coordinated changes across multiple domains. These results underscore the relevance of advanced smart technologies for assessing motor function in realistic and cognitively demanding contexts, providing a methodological and conceptual foundation for designing human-centered collaborative systems that both support and challenge human capabilities.

The present investigation should also be interpreted within the context of an exploratory multimodal framework. Rather than testing a single narrowly defined physiological variable, the study aimed to examine how different components of the sensorimotor system respond to collaborative and cognitively demanding task conditions. For this reason, multiple complementary measurement domains were included, each capturing a distinct dimension of human performance. This approach reflects the inherently distributed nature of motor control in HRC, where posture, muscle activation, movement organization, and visual attention interact to support task execution.

Despite the methodological rigor and the richness of the dataset, the study did not reveal systematic differences across conditions for all measured variables. Rather than reflecting limitations in data quality or acquisition procedures, this outcome highlights a fundamental methodological consideration in multimodal research: as experimental complexity and ecological validity increase, the ability to isolate condition-specific effects can decrease. The integration of multiple measurement domains resulted in a high degree of analytical density, with numerous variables, conditions, and segmentation strategies required to describe the task. Consequently, variations in the measured metrics may reflect distributed adaptations across domains or subtle interactions rather than pronounced effects in any single modality. Furthermore, the task design incorporated several elements aimed at enhancing realism and cognitive engagement, including interaction with a robotic partner, externally imposed timing cues, and stop-signal events. While ecologically valid, these elements increased protocol complexity, making it challenging to attribute observed effects to specific task components or interaction modalities. This trade-off between ecological validity and analytical tractability underscores the need for careful experimental design: realistic and engaging scenarios can produce rich data but may also obscure direct condition-dependent effects when analyzed using traditional statistical comparisons. From a methodological perspective, this work emphasizes that multimodality is not inherently advantageous: its effectiveness depends on the clarity and structure of the experimental design. Without clear prioritization of research questions and measurement domains, relevant trends may remain embedded within a dense analytical framework, thus limiting interpretability.

Future studies could further enhance interpretability by segmenting the task into meaningful sub-phases (e.g., reaching, picking, transporting, stopping) and performing time-resolved analyses, which would allow the identification of transient or phase-specific adaptations. Similarly, incorporating complementary or advanced metrics – such as nonlinear postural dynamics, inter-muscular coordination patterns, multidimensional kinematic smoothness, or gaze–motor synchrony – could capture subtler or distributed strategies that are not evident when signals are averaged across entire trials. Integrative multimodal analyses combining these metrics across diverse domains may provide a more complete characterization of adaptive behaviors in realistic HRC scenarios.

In conclusion, this study provides both substantive and methodological insights. Substantively, the results demonstrate that HRC fundamentally reshapes human sensorimotor and cognitive behavior, highlighting the redistribution of task demands rather than a simple reduction of physical effort. Methodologically, the findings illustrate the challenges of translating laboratory-based multimodal assessment approaches to realistic collaborative scenarios, emphasizing the importance of balancing ecological validity, experimental control, and interpretability. Future work should consider strategies to manage analytical complexity, such as prioritizing specific measurement domains, employing multivariate or integrative analysis approaches, or simplifying task design to isolate critical effects, thereby enhancing the interpretability and impact of multimodal HRC research.

5

Prediction of upper-limb movement direction: a step toward adaptive assistive robotics

This chapter investigates the key factors influencing EMG-based classification of upper-limb reaching movements, with the overarching goal of the development of hybrid robotic rehabilitation systems. Within the framework of the central hypothesis of this thesis, EMG signals are conceptualized as internal manifestations of motor intention, providing a window into neuromuscular adaptation. The study systematically examines how methodological choices – including muscle selection, temporal segmentation, feature extraction, classifier type, and validation strategy – affect the ability to decode movement intention from EMG signals only. Understanding how these components interact is essential for designing EMG-driven controllers capable of supporting timely and user-specific robotic assistance in neurorehabilitation contexts, where the restoration of voluntary motor function requires the ability to capture and respond to underlying neuromuscular adaptations.

Section 5.1 introduces the motivation and clinical relevance of the study, outlining the importance of accurately decoding motor intention for assistive and rehabilitative technologies.

Section 5.2 details the materials and methods used in the study: participants' characteristics (5.2.1), experimental protocol (5.2.2), experimental setup (5.2.3), data analysis (5.2.4), and statistical analysis (5.2.5).

Section 5.3 presents the results, and section 5.4 provides an in-depth discussion of these findings.

Section 5.5 concludes the chapter by summarizing the key insights gained from this analysis, highlighting the importance of metrics choice and encouraging future work exploring adaptive techniques to improve generalization across users.

5.1 Motivation and clinical relevance

A critical prerequisite for developing effective assistive robotic systems is the ability to quantify, in a systematic and objective way, the key parameters underlying motor intention and movement execution. In particular, understanding when and how a user initiates a movement, as well as the dynamics of the action, is essential to design robots that can respond accurately and in real time to the individual's needs. This knowledge is especially important in neurorehabilitation, where restoring upper-limb function is a central goal for individuals recovering from conditions such as stroke, which affects over 100 million people worldwide [339]. Promoting motor recovery after stroke relies on the brain's ability to re-establish the association between motor intention and its sensory consequences. Therefore, effective post-stroke rehabilitation requires task-oriented and high-intensity training, usually with an active participation of the patient to strengthen this link and support neuroplasticity [340], [341]. Consequently, considerable research efforts focused on developing robotic systems that integrate neuromuscular sensing and robotic actuation to aid rehabilitation of impaired upper limbs [342], [343].

Many of these systems exploit EMG signals to detect user intention, enabling real-time adaptation of robotic assistance to the individual's needs. Such approaches have the potential to accelerate motor re-learning and increase patient engagement [344]. Recent advancements also have shown that combining EMG-triggered Functional Electrical Stimulation and robotic technologies (referred to as Hybrid Robotic Rehabilitation Systems) has demonstrated superior efficacy compared to conventional therapy in improving post-stroke arm function and dexterity [345], [346], [347]. Furthermore, training in lifelike scenarios, where participants can freely interact with the environment, may further optimize motor gains [348].

Hybrid robotic systems ideally guide or assist the user's arm in the desired direction, according to both the user's intention and the level of assistance required, which depends on the user's capabilities. Several EMG-based solutions have been proposed to detect movement onset and decode user's intention, and they have been successfully applied to control prostheses and rehabilitation robots [349], [350]. Previous research has shown that, in controlled environments, EMG signals from shoulder muscles can discriminate the final reaching target [351], while more advanced processing enables classification even in unconstrained scenarios [352].

Despite these advances, EMG-based control faces persistent challenges due to the inherent variability of the signals. As systematically outlined by De Luca [353], this variability arises from both technical factors – such as electrode placement [354], crosstalk, and instrumentation noise – and physiological factors – such as fatigue [355], inter-individual anatomical differences, and motor unit properties. Beyond these intrinsic sources of variability, methodological decisions also critically influence classification performance. In particular, the choice of EMG features [356] and the classifier type [357] play a central role in accurately detecting movement intention. Moreover, EMG features are typically extracted over a predefined time window that segments the data series, whose length directly influences the amount of information captured: short windows may lack sufficient discriminatory power, while long windows can compromise real-time control [358].

Beyond these technical considerations on signal processing, validation methodology also substantially impacts the accuracy and the generalizability of EMG-based models. Most studies use holdout or intra-subject validation, which can overestimate performance in clinical settings [359]. Additionally, performance often decreases when transitioning to inter-subject validation methods, such as Leave-One-Subject-Out (LOSO) cross-validation, highlighting the need for personalized calibration or adaptive approaches like transfer learning, particularly in populations with diverse post-stroke motor deficits [360].

Considering these challenges, the present study systematically investigates five key factors affecting classification accuracy: type of classifier, number of muscles, number of features, time window length, and validation method. Methodological configuration is hypothesized to significantly influence EMG classification performance, reflecting the sensitivity of decoding models to analytical choices in signal processing. Increasing the amount of informative EMG content – through longer time windows, a greater number of muscles, and richer feature representations – is expected to improve classification accuracy. Moreover, performance is expected to be affected by classifier type and validation strategy, reflecting potential differences in how algorithms handle high-dimensional EMG feature spaces and extract patterns of motor intention. By examining how these key elements interact, this study provides practical recommendations for designing EMG-based control models. Although the study focuses on predicting reaching movements for future hybrid robotic rehabilitation, the findings are broadly applicable to a wide range of EMG-driven systems, including assistive robotics, neuroprosthetics, and human–machine interfaces in general.

5.2 Materials and methods

5.2.1 Participants

Twenty-two healthy individuals (12 females and 10 males, all right-handed, mean ± std – age: 25.77 ± 3.79 years, height: 171.95 ± 6.8 cm, 65.17 ± 9.60 kg) participated in the experiments. All participants were recruited in accordance with the ethical guidelines outlined by the Declaration of Helsinki. Written informed consent was obtained from each participant, and the study procedures were approved by the Ethical Committee of Roma Tre University.

5.2.2 Experimental protocol

Participants were seated comfortably on a chair with their dominant arm relaxed in a resting position, as illustrated in Figure 44.

Figure 44. Image photo of one subject at the resting position.

From this starting position, with the elbow flexed and the shoulder internally rotated to form an L-shape, participants were instructed to perform 10 repetitions of reaching movements toward a specific target in a 3D space. This task was repeated for 9 different target locations in a randomized order, resulting in a total of 90 reaching movements per participant. All targets for one participant can be visualized in Figure 45, with subplots arranged from top-left (#1) to bottom right (#9) corresponding to the target locations, which were set based on each participant's shoulder angle. The targets, identified by a frame placed on a table in front of the participant, were defined relative to the user central position with the arm raised forward, the shoulder flexed to 90°, and horizontally adducted to 90°. Starting from this position (central target – #5), eight additional targets were defined: up (110° shoulder flexion – #2), down (75° shoulder flexion – #3), left (-25° shoulder horizontal adduction – #4), and right (+20° shoulder horizontal abduction – #6), as well as four diagonal targets combining vertical and horizontal directions (#1, #3, #7, #9).

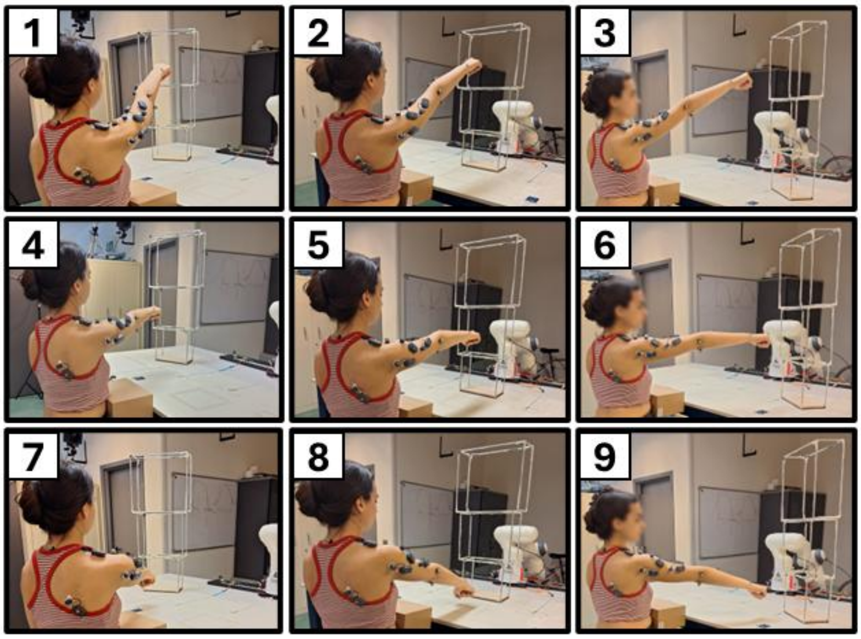

Figure 45. Image photos of the 9 target locations for the reaching movements. Targets are defined relative to a central position (center subplot – #5) with varying degrees of shoulder flexion (along the vertical dimension) and horizontal adduction (along the horizontal dimension). Subplots are arranged from top-left (#1) to bottom-right (#9).

Each movement consisted of four phases: (I) moving the arm to the target position, (II) holding the arm at that position, (III) returning to the resting position, and (IV) resting. Each repetition lasted exactly 6 seconds, where the moving phases (moving to and from the target location) lasted 1 second each, and the holding and resting phases lasted 2 seconds each. Each phase of the reaching movement was paced using a metronome to ensure consistent timing across tasks and participants. The metronome provided auditory feedback at 60 beats per minute, guiding participants to initiate and complete each repetition within a standardized timeframe. This approach aimed at minimizing variability in movement execution and ensured uniformity in data collection. Before starting the experiment, each participant familiarized with the reaching movements and the timing of the metronome.

5.2.3 Experimental setup

Kinematic data were collected using a stereophotogrammetry motion capture system with 8 cameras (SMART DX 6000, BTS Bioengineering). Data from 9 markers were acquired with a sampling frequency of 250 Hz. Markers were placed on bony prominences on the following points: neck, low back, clavicula, shoulder, internal and external elbow, internal and external wrist and on the hand. The hand marker was placed on the capitate bone, and the inner wrist marker was aligned vertically with the hand marker at the wrist midpoint to prevent occlusion during experiment [361]. Surface EMG signals were recorded from ten muscles on the dominant side using bipolar electrodes (FREEEMG 2000, BTS Bioengineering) at a sampling frequency of 1000 Hz. Muscles included brachioradialis, biceps (long and short), triceps, pectoralis (clavicular head), deltoids (anterior, medial, posterior), upper trapezius and teres major, as shown in Figure 52 and 53.

5.2.4 Data analysis

All data processing and analysis was performed in MATLAB (MathWorks, Natick, MA). Kinematic data were interpolated with cubic spline when markers were occluded and they were filtered with a low pass filter (3rd order Butterworth, cutoff frequency 3 Hz). EMG signals were bandpass filtered (3rd order Butterworth, 20-450 Hz) and ECG interference was removed from EMG signal with an adaptive template subtraction algorithm [362]. The EMG envelopes were extracted with an average moving window of 250 ms, allowing EMG-based segmentation to capture the temporal dynamics of muscular activity directly from the EMG signals.

In parallel, a marker-based segmentation was applied using kinematic data from the AP coordinate of the marker placed on the internal wrist. This segmentation defined the start and the end of each reaching movement based on eternal kinematic events, providing precise temporal boundaries for analyzing movement phases. First, velocity was computed through derivation. Then, a threshold was manually selected to identify the minimum velocity at which the relevant movement started, and it was used to detect the onset of each repetition. EMG signals were segmented starting from 150 ms before the identified movement onset (i.e., movement preparation) to account for the initiation of relevant movement and to consider the electromechanical delay effect [363]. Once the initial point was identified, features were extracted according to the time window length used.

For this purpose, a third segmentation approach was applied for the classification analysis. Starting from the initial point, 20 different time window lengths have been defined, ranging from 50 to 1000 ms with a step of 50 ms. For each muscle, the EMG signal was segmented in the specific time window, and from each muscle a set of 13 features – which are usually computed for the detection of reaching movements [364], [365], [366], [367] – was extracted: normalized envelope, mean frequency, median frequency, zero crossing, slope, integrated absolute value, mean absolute value, simple squared integral, variance, root mean square, waveform length, logarithm, slope sign change. For the normalization of the envelopes, the maximum value of the envelope of each muscle during the movement towards the top left target was used. Once all these features were extracted from each muscle, data were organized into a comprehensive table with 1980 rows, corresponding to 10 repetitions × 9 locations × 22 subjects, and 131 columns, representing 13 features from each of the 10 muscles plus one column for the response variable (i.e., the target location label). Each row thus contained a complete set of features for a single reaching movement. This process was repeated for each of the 20 analyzed time windows, resulting in 20 different feature tables, with each one of them having same structure but containing features computed over a specific temporal segment.

Then, a statistical analysis was performed to investigate which features and which muscles were the most important for the classification task. For each table, a Kruskal-Wallis test was used as a feature ranking algorithm to determine which were the most important predictors for the classification problem of distinguishing among different target locations [368]. The test results were transformed using the formula: $RV = -\log(p)$, where RV is the Ranking Value, and p is the p-value of the statistical test. The lower the p-value, the higher the RV, indicating a greater statistical significance of the feature in distinguishing target locations. Using this approach, all 130 features were ranked and sorted by their importance for classification purposes. Of these, the top 30 features were selected. To assess the contribution of each muscle, we counted how often features from each muscle appeared among the top 30, assigning a number to each muscle (i.e., the number of occurrences of that muscle in the 30 features). Since this counting process was performed across all time windows, it generated a comprehensive 20×10 matrix. From this matrix, all the counting frequencies were summed up across the time windows, obtaining a single value for each muscle, representing the total occurrences of the specific muscle across all time windows. The highest values revealed which muscles were the most important (based on feature importance analysis), and thus which were the most relevant muscles for the classification of the target locations. The entire process is illustrated in Figure 46.

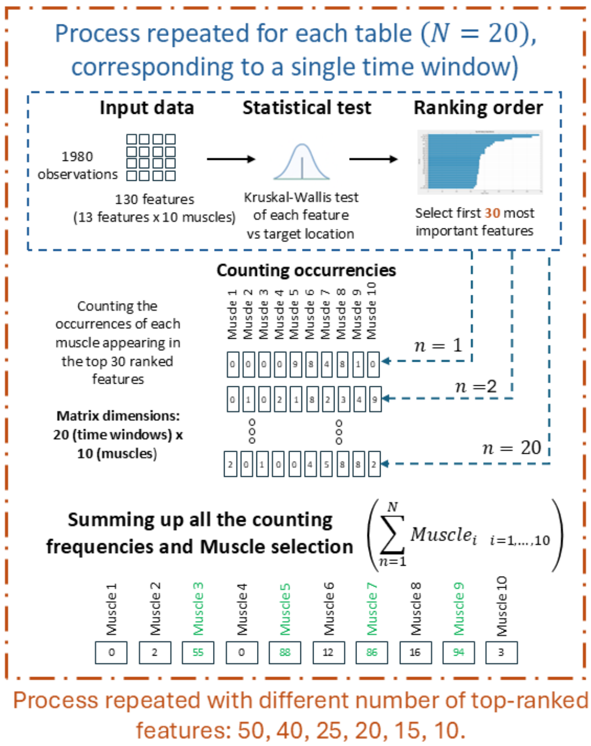

Figure 46. Graphical representation of muscle importance analysis for the selection of the most important muscles.

A similar and complementary approach was applied to determine the most important features, regardless of the muscle. By counting the occurrences of each feature type in the top 30 rankings for each time window, a 20×13 matrix was obtained. Summing up again across time windows, the counting frequency of the features revealed which were the more important ones. This entire process was repeated seven more times, each selecting a different number of top-ranked features: 50, 40, 25, 20, 15, 10, and 5 features (instead of the initial 30). The same analysis was performed for each set of top-ranked features to assess whether the initial number selection of top-ranked features influenced the results. Across all sets, the most important muscles and features remained largely consistent, indicating that the choice of threshold did not impact the ranking outcome. Therefore, the rest of the analysis has been conducted using the set of top 30 features.

Three machine learning algorithms were designed, then trained and validated: Fine Gaussian Support Vector Machine (SVM), k-Nearest Neighbors (KNN), and Bagged Tree (BT). For the design of the SVM algorithm, a multiclass error-correcting output codes model using SVM binary learners was trained; in the implementation, the Kernel function to Gaussian and the default one-versus-one coding design were used [369]. For the design of the KNN, the settings were: euclidean distance, ten neighbors, and the distance weight as squared inverse. For the design of the BT, the number of learning cycles was set to 30, and the maximum number of splits to 127 (default Matlab values). Each algorithm was tested under two validation methods: LOSO cross-validation and holdout 10-fold cross validation with an 80-20 split. Starting with a single muscle and one feature (the most important ones), the algorithms were tested with increasing numbers of features – from 1 to 5 – for the same muscle. The process was repeated for combinations of 2 muscles and 1 feature, then 2 muscles and 2 features, and so on, up to 5 muscles and 5 features. This analysis was performed 20 times, one for each time window. This systematic approach resulted in five different 5 × 20 accuracy matrices for each muscle. To facilitate visualization of the results, these matrices were combined into a single 25 x 20 matrix to generate heatmaps. Each of these comprehensive matrices was calculated for each classifier under both the validation methods. The value in the matrices represented the average accuracy across all participants for LOSO validation and the average accuracy across 10 random seeds for holdout validation.

5.2.5 Statistical analysis

Normality was assessed using the Shapiro–Wilk test, which showed significant deviations for all classifiers ($p < 0.05$), motivating the use of non-parametric statistics. Classifier performance was compared only under the holdout validation strategy, as LOSO accuracy never exceeded 35% and was therefore excluded from meaningful analysis. For the holdout approach, all accuracy values across muscles, features, and window lengths were aggregated into a single vector per classifier, yielding a repeated-measures design with three related groups. To focus on practically relevant performance levels, only accuracy values above 50% were retained. Overall differences among classifiers were tested with a Friedman test, followed – when significant – by Wilcoxon signed-rank pairwise comparisons with Bonferroni correction. The significance level was set to 0.05 (*).

5.3 Results

The muscle importance analysis revealed that 5 muscles consistently appeared in the top-ranking features: pectoralis major, anterior deltoid, posterior deltoid, trapezius, and medial deltoid, ranked in descending order of importance. The feature importance analysis revealed that the 5 most frequently selected features for the classification were: slope, normalized envelope, variance, simple squared integral, and root mean square, ranked in descending order of importance. Because these outcomes were highly consistent across all tested sets of top-ranked muscles and features, subsequent analyses focused exclusively on these five most important muscles and features.

Figures 47-52 illustrate the heatmap summarizing the classifiers' accuracy values with the two distinct validation methods: BT with LOSO in Figure 47, KNN with LOSO in Figure 48, SVM with LOSO in Figure 49, BT with holdout in Figure 50, KNN with holdout in Figure 51, SVM with holdout in Figure 52. For each heatmap, the x-axis indicates the time window length in milliseconds, while the y-axis represents the number of features used for the analysis, with curly brackets indicating the number of muscles from which the features were extracted. Color intensity follows the Batlow scale, progressing from low values of accuracy in deep blue to high values of accuracy in bright yellow, ensuring perceptual uniformity and accessibility [370].

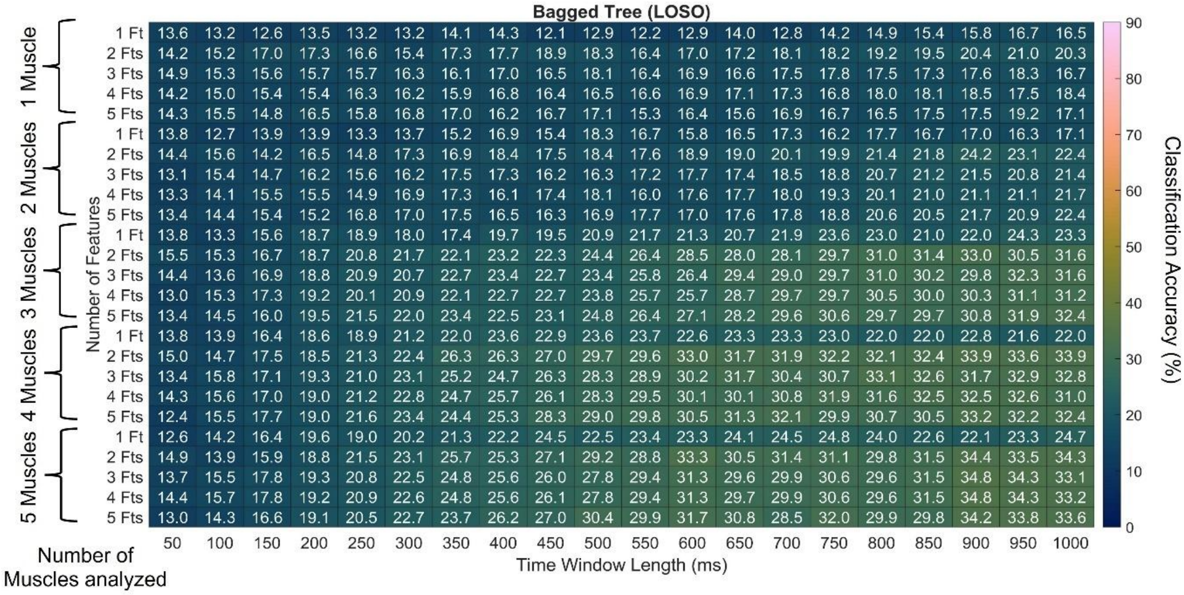

Figure 47. Heatmap summarizing the BT classifier accuracy with the LOSO validation method.

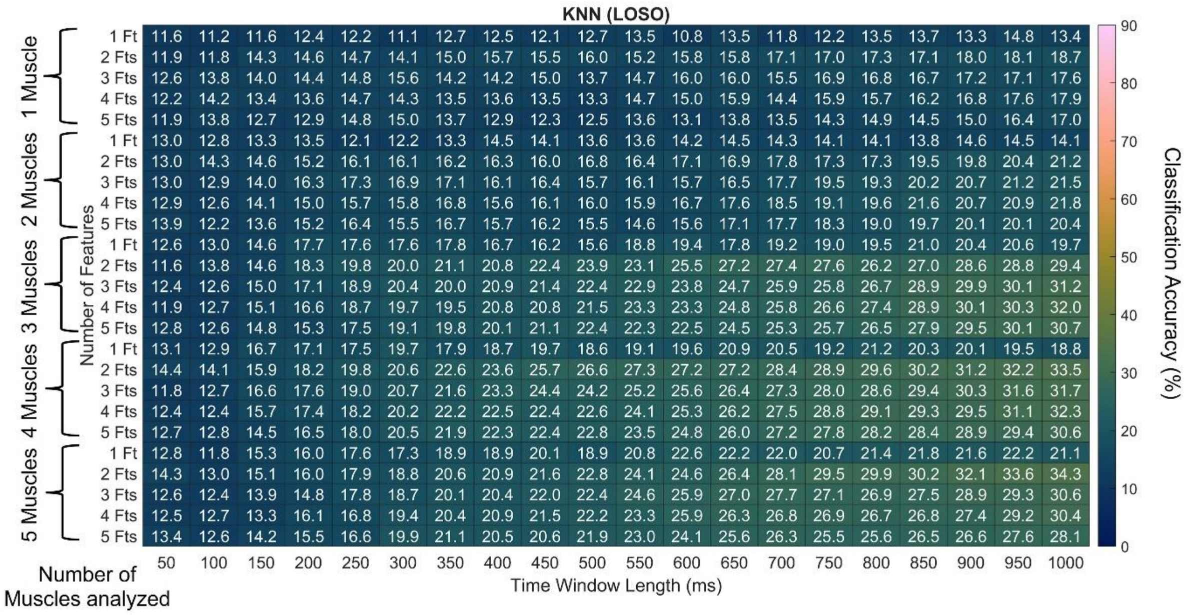

Figure 48. Heatmap summarizing the KNN classifier accuracy with the LOSO validation method.

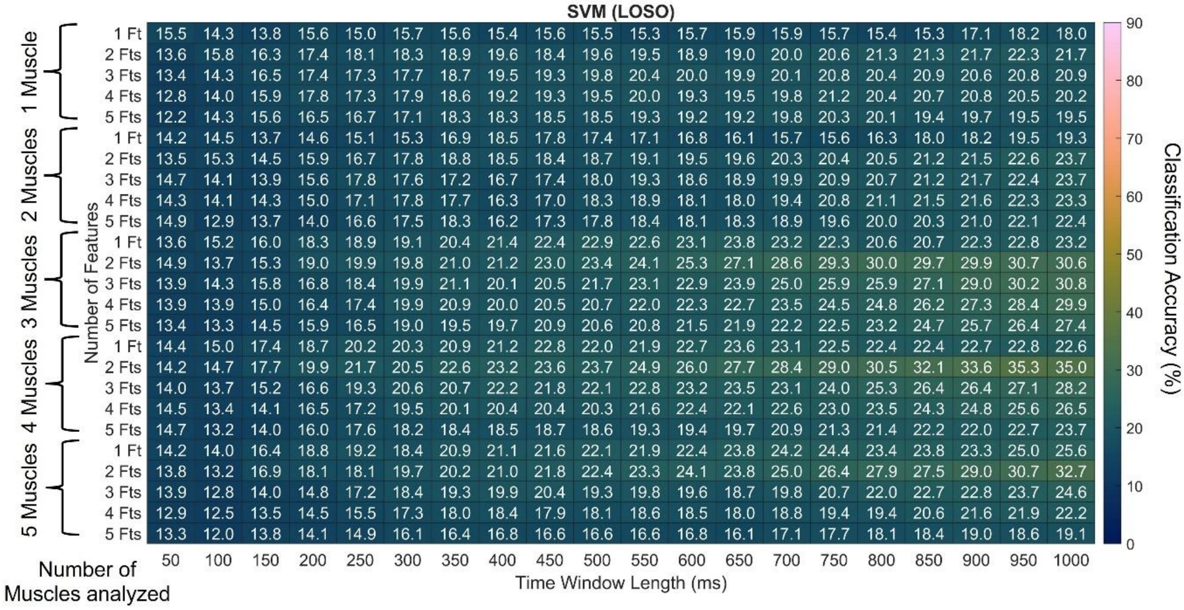

Figure 49. Heatmap summarizing the SVM classifier accuracy with the LOSO validation method.

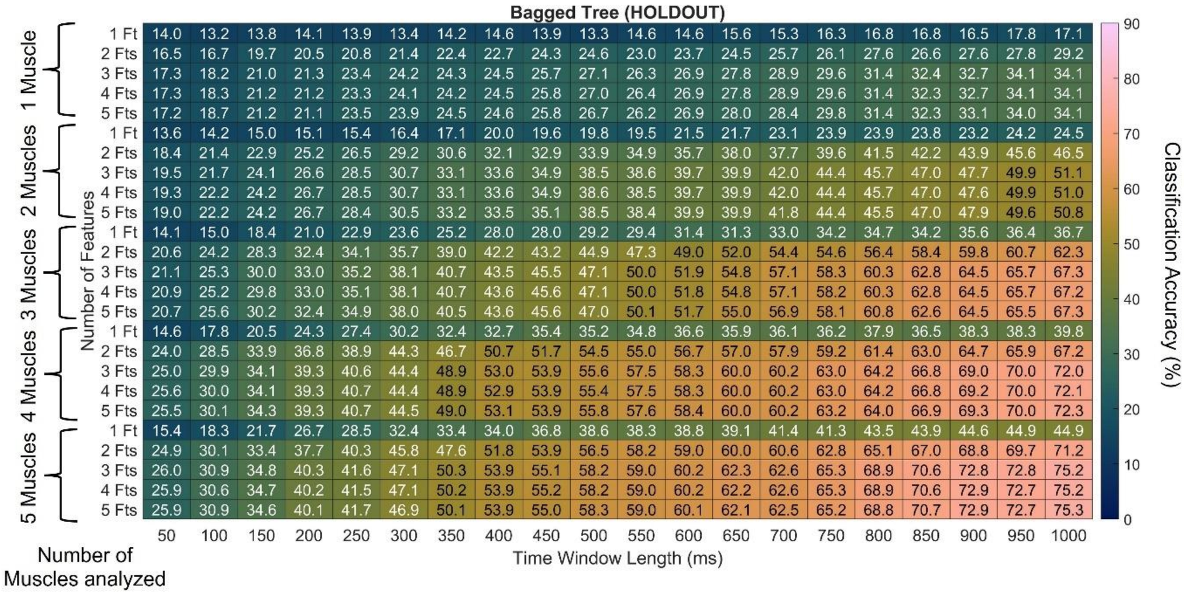

Figure 50. Heatmap summarizing the BT classifier accuracy with the HOLDOUT validation method.

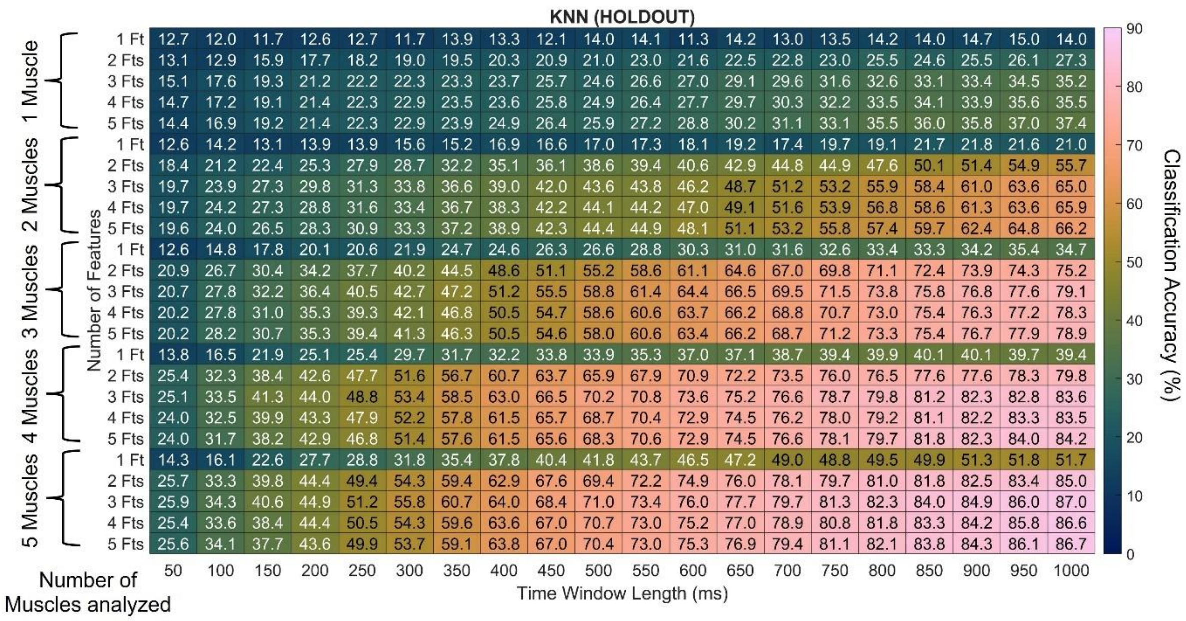

Figure 51. Heatmap summarizing the KNN classifier accuracy with the HOLDOUT validation method.

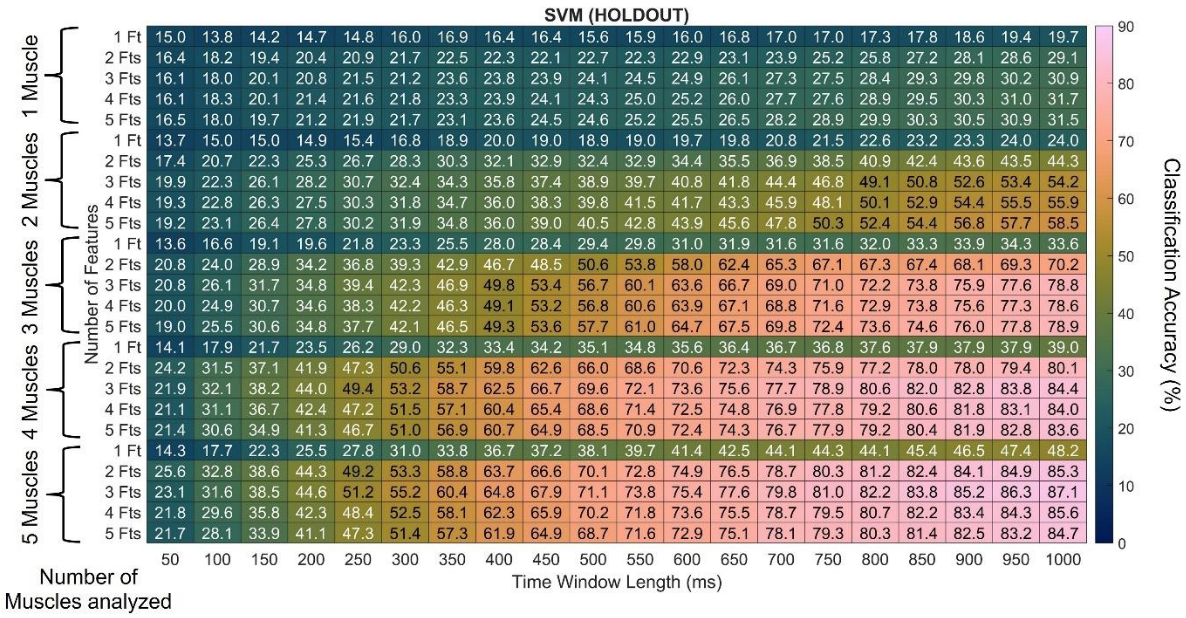

Figure 52. Heatmap summarizing the SVM classifier accuracy with the HOLDOUT validation method.

Analysis of heatmaps reveals some clear trends. First, time window length strongly influenced classification accuracy: shorter windows consistently resulted in poorer performance, with accuracy starting to improve noticeably for windows between ~300 and 600 ms (~150–450 ms after movement onset). Longer windows increased accuracy, peaking near the end of the task's dynamic phase, a trend consistent across all classifiers, validation methods, and muscle–feature combinations. Second, accuracy increased with the number of features, particularly under the holdout method. The largest improvement occurred when moving from one feature (i.e., slope) to two (i.e., slope and normalized envelope), while additional features provided only marginal gains, suggesting diminishing returns. Third, including more muscles enhanced performance: accuracy consistently rised from top to bottom rows in all heatmaps, indicating that a larger muscle set provides additional discriminative information for predicting the final target location. The validation strategy also plays a critical role: LOSO remains challenging, producing consistently low accuracy across classifiers, whereas the holdout method yields a wider range (~15% to ~85%), making the effects of muscles, features, and time windows more apparent. Finally, classifier type impacts accuracy: both KNN and SVM outperform BT, especially under holdout validation. Differences among classifiers in LOSO are negligible due to uniformly low accuracy, while statistical analysis with a non-parametric Friedman test confirmed a significant difference among classifiers ($p < 0.001$) under the holdout method, with post-hoc comparisons showing BT performing significantly worse ($p < 0.05$) than KNN and SVM, which are comparable (Figure 53).

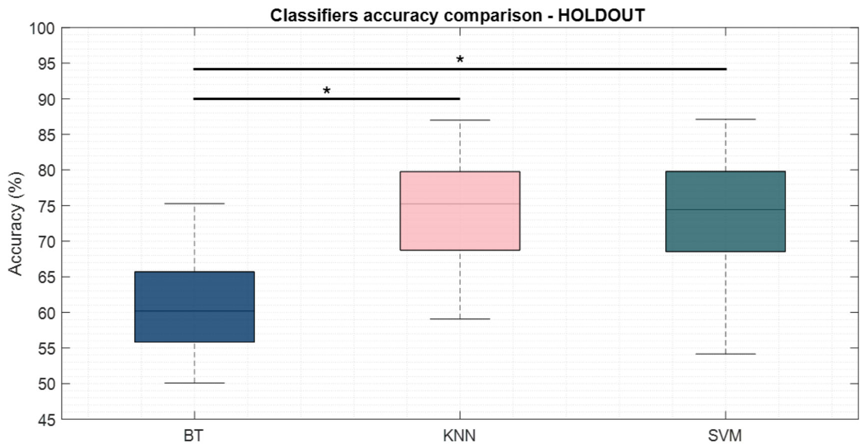

Figure 53. Comparison of classification accuracies with the three different classifiers under the holdout validation.

5.4 Discussion

This study systematically examined the impact of five key factors on EMG-based classification of reaching movements, with potential applications in robotic rehabilitation: time-window length, number of features, number of muscles, validation strategy, and classifier type. The findings provided clear insights into the relative importance of these elements for optimizing model performance and designing practical EMG-based control systems. The results showed that the classifiers accurately decoded movement directions toward predefined targets, enabling goal-oriented classification beyond simple movement intention detection and supporting the development of adaptive robotic assistance, despite some inherent methodological constraints. However, the relative contribution of each factor was not uniform, revealing a hierarchy of importance and practical constraints that nuance this general effect.

Time-window length emerged as a critical determinant of classification accuracy. Short windows (< 250 ms) consistently yielded poor performance, likely because early phases of movement preparation and execution do not yet exhibit sufficiently distinct EMG patterns to reveal movement intentions. A 250 ms window corresponds to approximately 100 ms after movement onset, thus capturing initial EMG activity but lacking discriminative information for predicting the final target location. Thus, accuracy improved substantially with longer windows. However, practical applications in hybrid robotic control impose constraints: longer windows introduce delays, which may reduce responsiveness. A window of ~500 ms (~350 ms after movement onset) represents a feasible compromise, capturing sufficient discriminative information while still allowing timely robotic assistance during partially assisted movements. These findings underscore the importance of temporal design in EMG control architecture: window length should not be treated as a static parameter but as a design element that interacts with the requirements of specific applications. Temporal design choices shape the trade-off between information richness and responsiveness, influencing how effectively intention-driven systems can operate in real time. Rather than assuming a universal configuration, the results suggest that this parameter selection must be guided by the operational context of the application, particularly in interactive and rehabilitation-oriented scenarios where timing constraints are critical.

The number of features also influenced classification outcomes, especially when adding the second most important feature. Beyond this, other additional features offered minimal gains and might even introduce redundancy or misleading associations. These findings highlight that a small, carefully selected feature set can capture the most discriminative information while reducing computational complexity, facilitating faster training and lower processing demands – an important consideration for real-time control in rehabilitation contexts. Similarly, the number of muscles significantly affected model performance: including more muscles consistently improve accuracy, even more than the case in which more features were extracted from the same muscle set. This indicates that multi-muscle recordings capture complementary information crucial for discriminating subtle differences in reaching direction, suggesting that careful selection of the correct set of muscles is more effective than increasing feature complexity and highlighting that not all sources of additional information contribute equally to performance.

The validation strategy revealed a fundamental challenge: inter-individual variability in EMG signals. Holdout validation, which trains and tests data from the same participants, produced high accuracy but primarily reflects performance with “known” users. In contrast, LOSO validation, which tests the model on entirely new participants, yielded much lower accuracy, highlighting the limited generalizability of models across individuals. This discrepancy underscores the necessity of subject-specific pre-calibration for real-world deployment, particularly in clinical or assistive applications. Future studies may explore strategies such as transfer learning or individualized fine-tuning to enhance cross-subject robustness.

Finally, classifier type influenced classification performance, though to a lesser extent than the other factors discussed above. Under holdout validation, SVM and KNN significantly outperformed BT, likely due to their capacity to handle high-dimensional nonlinear EMG feature spaces (for SVM) and non-parametric distributions (for KNN) [371]. However, under LOSO validation, all classifiers achieved low accuracy, with differences among them being negligible. Interestingly, BT benefited slightly from additional features, whereas KNN and SVM performance varied more with longer windows due to inter-subject variability. These findings indicate that classifier selection is important for optimizing performance in task-specific scenarios but cannot compensate for insufficient input data or inadequate windowing.

In practical terms, the results show that EMG classification performance depends primarily on informational sufficiency and generalization constraints rather than on classifier selection alone. A limited set of well-chosen features and muscles, combined with an appropriately sized time window, can achieve meaningful performance, whereas adding redundant features yields diminishing returns while increasing spatial EMG diversity provides substantial gains. Time-window length must balance discriminative power with real-time responsiveness, and subject-specific calibration remains essential for reliable cross-user application. Overall, the findings confirm that methodological configuration systematically shapes performance, highlighting the importance of informational richness, demonstrating generalization constraints across individuals, and showing that classifier type influences but does not dominate outcomes. Rather than identifying a universally optimal setup, these results underscore the need to tailor EMG decoding strategies to task- and application-specific constraints, particularly in rehabilitation-oriented human–robot systems.

5.5 Conclusions

This study investigated key factors influencing EMG-based classification of reaching movements, aiming to identify configurations that optimize performance while remaining practically feasible. Complementing the other studies in this thesis, it focused on the neuromuscular component of motor behavior to assess the predictive potential of EMG signals for anticipating upper-limb movement intentions. The novelty of this work lies in the systematic and structured evaluation of methodological parameters that are often treated as fixed or secondary choices in EMG classification studies. Rather than applying machine learning pipelines as black-box solutions, this study critically examined how specific signal-processing and validation decisions influence classification robustness and translational applicability.

The results demonstrate that multi-muscle recordings combined with a minimal but robust feature set (including EMG slope and normalized envelope) provide the most discriminative information for target classification. Time-window length is also critical, with ~500 ms windows (~350 ms after movement onset) striking a practical balance between classification accuracy and near-real-time responsiveness, which is essential for hybrid robotic systems assisting partially executed movements. By identifying a configuration that balances computational simplicity, interpretability, and performance, this study contributes practical guidelines for reproducible and deployable EMG-based intention decoding. A key finding is also the substantial difference in performance between Leave-One-Subject-Out cross-validation and holdout validation, highlighting limited inter-individual generalizability and emphasizing the need for subject-specific calibration in clinical applications. Importantly, this result suggests that motor intention signatures are highly individualized, supporting a personalized approach to EMG-driven human–robot interaction rather than universal classification models. This underscores the importance of tailoring smart technology assessments to individual motor patterns in innovative and collaborative environments.

While these findings provide important insights for EMG-based prediction of movement intentions, several limitations must be considered to contextualize their applicability and guide future research. First, all participants were healthy adults, limiting direct applicability to clinical populations, such as post-stroke or neurodegenerative patients, whose EMG patterns may differ substantially. Second, only a predefined set of features and three classifiers were tested, leaving open the potential for alternative features (e.g., time-frequency, nonlinear) or advanced models (e.g., deep learning methods) to enhance classification. Third, the study examined only window length relative to movement onset; temporal placement within the movement may also affect discriminative power and should be explored in future studies. Moreover, the closed-set nature of the classification paradigm represents another limitation: untrained movements are assigned to the nearest class, with potential misclassification. This behavior has implications for safety and robustness in real-world use, where users may perform actions outside the predefined set, thus suggesting that integrating out-of-distribution detection could help prevent unreliable control actions. Finally, future extensions integrating multimodal signals may further enhance robustness by providing complementary information about movement dynamics and environmental context, enabling a richer and more reliable intention-detection framework capable of distinguishing genuine user goals from noisy or ambiguous EMG patterns.

These findings demonstrate that carefully selected muscles, a few robust EMG features, and appropriately sized time windows can reliably predict reaching intentions in real time, despite inter-individual variability. By highlighting both the feasibility and limitations of EMG-based classification in hybrid rehabilitation, the study establishes a foundation for using muscular signals to enable adaptive intention-driven human–robot interaction. Conceptually, the results support a shift from generic intention-detection models toward personalized, calibration-based decoding strategies that reflect the intrinsic variability of human motor control. Such approaches can inform the design of human-centered robotic systems that respond dynamically to users' motor states, promoting more efficient, intuitive, and personalized rehabilitation and collaborative interventions. Overall, the study underscores the value of EMG sensing as a smart tool for assessing and anticipating human motor behavior within technologically enriched innovative and collaborative environments.

6

Final Conclusions

6.1 General discussion

This doctoral research investigates how smart technologies can be employed to quantitatively assess and interpret human behavior in innovative and collaborative contexts, spanning healthcare and industrial environments. While the individual studies focus on different technologies and experimental paradigms, they are connected by a common conceptual framework: understanding how technologically mediated environments reveal mechanisms of human adaptation. Rather than treating these technologies as isolated domains, the thesis frames them as complementary experimental perturbations that disclose different levels of a common adaptive motor system. This integrative perspective enables the investigation of human behavior as a distributed phenomenon expressed across multiple levels of control, from sensorimotor organization to interactional regulation and neuromuscular activity. Importantly, these technologies are not only used as measurement instruments, but as structured experimental contexts that make latent adaptive processes observable. This represents a conceptual contribution of the thesis, supporting the interpretation of smart technologies as tools for revealing, rather than simply quantifying, human motor adaptation.

Across four complementary studies, Virtual Reality, Human–Robot Collaboration, and EMG-based paradigms were used to investigate human performance from clinical, ergonomic, interactional, and neuromuscular perspectives. The results collectively show that technological systems can function both as experimental perturbations and as analytical interfaces for studying adaptive motor behavior. Importantly, the findings demonstrate that adaptation is not uniformly expressed across levels, but manifests through level-dependent dynamics that differ in sensitivity, stability, and informational content. Nevertheless, all of them collectively highlight the capacity of smart technologies to enable objective, multimodal, and ecologically grounded assessments of human motor behavior. A central outcome is that multimodal measurements are not redundant, but structurally complementary, as they capture distinct and distributed components of a single adaptive system. Kinematic, postural, cognitive, and neuromuscular measures therefore reflect different temporal and functional stages of motor control, requiring integrated interpretation rather than isolated analysis.

The first study used immersive VR to investigate sensorimotor adaptation in individuals with Alzheimer's Disease and Mild Cognitive Impairment. VR provided a controlled yet ecologically meaningful perturbation that revealed graded differences in kinematic performance across groups. The results confirmed that sensorimotor behavior is highly sensitive to cognitive impairment and task structure, with evidence of altered anticipatory strategies in clinical populations. These findings support the role of VR as a powerful tool for revealing sensorimotor-level adaptation. While limited to kinematic measures and specific task conditions, this study provides initial evidence that these adaptive processes can be systematically captured in clinical populations, contributing to the overarching goal of understanding human motor behavior as a multidimensional phenomenon shaped by interaction with innovative environments.

The second study investigated how Human–Robot Collaboration modifies postural control during dynamic manipulation tasks. The results showed that the presence of the robot induced systematic changes in balance regulation and movement variability, reflecting adaptive reorganization of postural strategies. However, these effects appeared more stable and less sensitive to fine-grained experimental manipulations than expected, suggesting that interactional-level adaptation follows more robust dynamics than clinical and sensorimotor-level behavior. This result refines the central hypothesis by indicating that different levels of the motor system may exhibit different sensitivity profiles to technological perturbations. These findings highlight both the ergonomic risks and the adaptive capacities involved in HRC, emphasizing the importance of designing cobots that support natural postural strategies.

The third study extended this perspective by integrating postural, muscular, kinematic, and eye-tracking measures to examine adaptation under varying cognitive and motor demands in HRC. The results demonstrated that adaptation is distributed across multiple domains and cannot be reduced to a single behavioral dimension. They also showed that HRC fundamentally reshapes human behavior, influencing motor planning, coordination, and attention rather than simply reducing physical effort. These findings demonstrate that humans continuously modulate motor behavior based on context, preparation, and external cues, balancing efficiency, stability, and responsiveness. Cognitive load, motor execution, and postural regulation interact dynamically, confirming that human performance in these collaborative environments emerges from the coupling of multiple subsystems. This further supports the notion of a distributed and context-sensitive adaptive system. At the same time, the study also highlighted that the richness of multimodal and cognitively demanding paradigms may introduce additional variability that can partially obscure condition-specific effects, underscoring the need for careful experimental design that balances ecological validity, analytical clarity, and interpretability.

The fourth study focused on EMG-based classification of reaching movements, systematically evaluating methodological factors affecting decoding performance. The results showed that neuromuscular signals contain highly informative but variable representations of motor intention, strongly influenced by feature selection and inter-subject variability. These findings confirm that neuromuscular-level information provides a sensitive but non-trivial substrate for predicting motor behavior, highlighting both its potential and its dependence on methodological configuration.

These studies have been designed to address a unified research question: how human motor behavior adapts when interacting with technologically mediated environments. Each study approached this question from a distinct level of the motor system: the first study confirms sensorimotor-level sensitivity to structured perturbations, the second reveals more stable interactional dynamics during human–robot collaboration, the third demonstrates the distributed nature of adaptation across multiple behavioral domains, and the fourth highlights the predictive but highly variable nature of neuromuscular signals. Despite differences in methodology and application domains, the findings converge in demonstrating that adaptation does not occur as a uniform response but varies across levels of organization. Sensorimotor, interactional, and neuromuscular processes follow distinct dynamics when exposed to technological perturbations, pointing to a multi-layered structure of human motor behavior with differentiated responses. From this perspective, smart technologies act as structured probes, uncovering complementary facets of a common adaptive architecture. Overall, the results support a coherent view of human behavior in technologically mediated environments as intrinsically adaptive yet expressed differently depending on the level of analysis. Rather than reflecting a single, unified adjustment, adaptation arises through ongoing recalibration of motor and cognitive strategies, shaped by the specific subsystem under observation.

Methodologically, the thesis highlights the importance of multimodal, quantitative, and complementary approaches that bridge laboratory assessment and real-world application. Kinematic, postural, cognitive, and neuromuscular measures provide non-redundant but converging insights into adaptive behavior. Overall, this research supports a level-dependent and embodied view of human performance, in which smart technologies function as experimental systems capable of revealing the hierarchical organization of motor adaptation. This perspective provides a foundation for the design of future rehabilitation, ergonomic, and human–robot systems that are explicitly grounded in the distributed and level-dependent nature of human motor behavior.

6.2 Strengths and limitations

This thesis contributes to scientific literature in several ways. Methodologically, it demonstrates the feasibility and value of multimodal, quantitative analyses combining different data across diverse contexts. This integrated framework enables a comprehensive assessment of human adaptation mechanisms and provides a blueprint for future research using sensor-based methodologies. The EMG-based classification study further illustrates how systematically varying experimental factors can optimize predictive performance and inform real-time applications in rehabilitation and collaborative robotics. From a theoretical perspective, the thesis advances understanding of human adaptation during interactions with virtual or robotic agents, revealing how cognitive, postural, and motor factors dynamically interact.

Findings across studies support the concept that adaptation is an active process of continuous recalibration in response to environmental and task constraints, rather than merely a compensatory mechanism. EMG analyses show that such adaptation is encoded not only in observable behavior but also in neuromuscular patterns, offering sensitive markers of task-specific motor strategies and cognitive engagement. Practically, the research provides empirical evidence and methodological insights relevant to rehabilitation and healthcare, where VR and EMG-based assessments can support personalized evaluation and training, and to industrial ergonomics, where HRC systems can be designed to optimize human safety, comfort, and efficiency. Furthermore, the experimental paradigms and analytical strategies developed across the studies represent methodological contributions in themselves, by translating collaborative and immersive tasks into measurable motor perturbations and integrating multimodal assessments. This approach allows precise quantification of how humans adapt their motor and cognitive strategies in interactions that closely resemble real-world scenarios.

Despite these strengths, several limitations should be acknowledged. A key limitation concerns the population sample, as three of the four studies were conducted on relatively small groups of healthy young participants, which limits the transferability of the findings to clinical populations or real-world industrial workers. Ecological validity represents another constraint, since all studies were performed in controlled environments; while this ensured precise measurements and high reproducibility, it may not fully capture the variability and complexity of real-life conditions. Task specificity must also be considered, as each study focuses on predefined movements or interaction scenarios, and the results may therefore not generalize to other motor tasks or functional activities involving different degrees of freedom or higher complexity.

An additional and important limitation relates to the presence of potential confounding factors across studies. In particular, the experimental investigations did not systematically control key variables such as participant age and type of technology. For example, virtual reality paradigms were tested on older adults, whereas human–robot collaboration scenarios involved predominantly young participants. As a result, multiple influencing factors were varied simultaneously, making it difficult to disentangle whether the observed effects are attributable to the technological environment, to age-related differences, or to their interaction. This lack of homogeneous comparison conditions limits the internal validity of cross-study interpretations and reduces the possibility of isolating the specific contribution of each factor to the observed outcomes.

The set of outcome measures constitutes a further limitation, as the analyses were restricted to selected postural, EMG, kinematic and gaze-related parameters, while other potentially informative metrics – such as neural activity, fatigue indices, more complex time–frequency EMG features, or more advanced predictive approaches – were not explored. Session duration also represents a limitation, as the relatively short experimental sessions prevented the investigation of long-term adaptation, learning processes, or cumulative effects of repeated exposure to virtual or collaborative environments. In addition, interpretation of results remains partially open, particularly in the HRC studies, where the lack of complementary longitudinal or contextual data makes it difficult to fully disentangle adaptive strategies from potential impairments. Finally, experimental setup variability may limit direct comparability across studies, as each experimental protocol involved specific technologies, task parameters, and environmental conditions.

Overall, these limitations highlight the need for future research involving larger and more diverse populations, the integration of real-world and longitudinal assessments, broader feature extraction strategies combined with advanced machine learning approaches, and a stronger emphasis on ecological validity. Addressing these aspects will enhance the generalizability and applicability of findings and further bridge the gap between technological innovation and human-centered design in both clinical and industrial contexts.

6.3 Final remarks

This thesis underscores the potential of smart technologies as powerful tools for both scientific investigations and practical applications, generating new knowledge on the multidimensional nature of motor behavior in technologically mediated environments. Smart technologies can serve as experimental frameworks to reveal adaptive motor–cognitive processes, rather than merely functioning as assistive or measurement tools. By embedding objective measures within technologically advanced environments, it becomes possible to capture the complexity of human behavior and the dynamic nature of adaptation during interaction with machines or external stimuli. The findings demonstrate that these measurements do not merely quantify performance but also reveal adaptive processes, providing evidence of how humans reorganize motor and cognitive strategies in response to technological constraints. This has significant implications for system design: technologies that acknowledge and respond to human adaptation can transition from passive measurement tools to active components of human-centered ecosystems. The findings support a broader vision of intelligent system design: one that is guided not only by automation and efficiency but also by a deep understanding of the human component. Within this perspective, the present work represents a step toward realizing truly human-centered smart environments: systems capable of interpreting, respecting, and enhancing human capabilities across healthcare, rehabilitation, and industrial domains.

A key contribution to this research is the integration of multimodal data to provide a comprehensive picture of human adaptation. This approach enabled not only the quantification of performance but also the identification of underlying mechanisms through which humans recalibrate motor strategies, maintain stability, and optimize task execution in response to novel technological conditions. Through the studies, participants consistently exhibited adaptive responses, reflecting the intrinsic flexibility and resilience of the human motor system. These responses were observable at multiple levels – from changes in muscle activation patterns to postural adjustments and movement kinematics – highlighting the richness of information captured through sensor-based methodologies. This demonstrates that multimodal assessment can directly inform practical decisions, such as which muscles to monitor for predictive control, which postural interventions may reduce ergonomic risk, and how to tailor collaborative tasks to individual capabilities. The work emphasizes the importance of personalization and subject-specific strategies. Particularly in the EMG-based classification study, substantial inter-individual variability revealed the need for calibration and adaptive approaches to ensure reliable performance across users. This insight has direct implications for the design of future rehabilitation and collaborative robotic systems, which should be capable of dynamically adjusting to individual motor patterns, cognitive states, and task demands, thereby promoting inclusive and effective interaction.

In addition to methodological and practical contributions, this thesis provides translational insights. In healthcare contexts, immersive VR combined with kinematic analysis demonstrated the potential to sensitively detect early sensorimotor deficits in neurodegenerative conditions and to support engaging, ecologically valid assessment and training paradigms. By enabling early detection of subtle motor changes in neurodegenerative conditions, the methodologies developed in this thesis provide a foundation for preventive and personalized healthcare approaches that complement traditional clinical assessments and support timely interventions to improve long-term functional outcomes. In industrial contexts, integrating different measures enabled a multidimensional evaluation of human adaptation in collaborative robotic environments, offering guidance for ergonomic design, safety optimization, and efficient task allocation. Looking forward, the findings highlight promising directions for the development of real-time adaptive systems that not only measure human performance but actively respond to and enhance motor function. These systems should be designed to complement human capabilities by dynamically adjusting to individual motor and cognitive states. This vision aligns with the broader goal of human-centered smart environments that enhance safety, efficiency, and inclusivity in both healthcare and industrial domains.

Future research should explore advanced machine learning and sensor fusion techniques, transfer learning for improved generalization, and strategies to optimize real-time responsiveness while maintaining accuracy. Longitudinal and ecological studies will be essential to capture adaptation over time and ensure the practical applicability of these systems in real-world settings. Extending research to longer-term deployments will help reveal how adaptation evolves beyond short experimental sessions and evaluate the sustained benefits of technology-assisted interventions, providing critical evidence for translating experimental insights into solutions with tangible societal and clinical impact.

This thesis contributes to a broader theoretical understanding of human performance in technologically mediated environments. By revealing how cognitive, perceptual, and motor processes are dynamically coupled and continuously recalibrated, it supports an embodied and adaptive view of human behavior. Collectively, the studies demonstrate that smart technologies can serve as both investigative tools and functional interfaces, offering a foundation for the design of intelligent, interactive, and inclusive systems capable of enhancing human capabilities across diverse contexts.

The results provide concrete, actionable insights for future applications. VR-based assessments can detect subtle motor impairments in clinical patients, enabling early intervention and tailored rehabilitation protocols. Collaborative robot tasks reveal specific postural and muscular adjustments that can inform ergonomic design and safe task allocation in industrial settings. Multimodal measurements offer predictive markers that can guide real-time adaptive systems, ensuring responsive assistance based on individual motor and cognitive states. These findings highlight that adaptation occurs across multiple subsystems, and monitoring a single domain may miss critical information, emphasizing the need for integrated, multimodal evaluation in both healthcare and industrial applications. More specifically, the following key contributions emerge from the thesis: *(i)* a practical framework showing that VR, HRC, and EMG sensing act as structured perturbations; *(ii)* evidence that human adaptation is multidimensional, with concurrent changes in postural control, neuromuscular coordination, movement patterns, and gaze behavior; *(iii)* concrete guidance for healthcare and industrial applications, including early detection and personalized rehabilitation, ergonomic optimization, and adaptive task allocation in collaborative robotic environments.

The central hypothesis of this thesis was not simply confirmed, but progressively refined across studies, revealing human motor adaptation as a distributed and level-dependent phenomenon, characterized by distinct dynamics across sensorimotor, interactional, and neuromuscular levels. Taken together, the results support a unified vision in which smart technologies serve not only as assistive tools, but as experimental ecosystems capable of revealing the complexity of human motor and cognitive adaptation. By integrating immersive VR environments, collaborative robotics, and neuromuscular sensing within a common analytical framework, this thesis contributes to a more coherent understanding of how human behavior emerges, adapts, and can ultimately be predicted within technologically enriched environments. In conclusion, this work reinforces the view of human–technology interaction as a bidirectional process, in which human adaptation informs technological evolution and technologies shape behavior, highlighting the importance of designing systems that are both technically effective and responsive to human needs.

List of Publications

Publications on peer-reviewed international journals

- G. Corvini, A. de Nobile, T. Del Grossi, C. De Marchis, M. Gandolla, E. Ambrosini, and M. Schmid, "EMG-based reaching prediction for upper limb rehabilitation: a systematic analysis of factors affecting the classification accuracy", *in revision at Journal of NeuroEngineering and Rehabilitation (2026)*
- A. de Nobile, D. Bibbo, S. Ranaldi, G. Corvini, and S. Conforto, "Dynamic Balance Control and Postural Adaptation in Human-Robot Collaborative Manipulation: Within-Subject Experimental Study", JMIR Human Factors (2026)
- A. de Nobile, I. Borghi, P. De Pasquale, D. Berger, A. Maselli, F. Di Lorenzo, E. Savastano, M. Assogna, A. Casarotto, D. Bibbo, S. Conforto, F. Lacquaniti, G. Koch, A. D'Avella, and M. Russo, "Anticipatory reaching motor behavior characterizes patients within the Alzheimer's disease continuum in a virtual reality environment", Alzheimer's Research & Therapy (2025)
- A. de Nobile, D. Bibbo, M. Russo, and S. Conforto, "A focus on quantitative methods to assess human factors in collaborative robotics", International Journal of Industrial Ergonomics (2024)

Publications on proceedings of national and international conferences

- F. Forconi, I. De Meis, A. de Nobile, M. Schmid, S. Conforto, and S. Ranaldi, "Mapping forearm muscle activity with a single linear HD-EMG grid and muscle synergy model during hand-wrist movements", 2025 47th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)
- E. M. Fiorino, A. de Nobile, D. Bibbo, G. Corvini, S. Ranaldi, S. Conforto, and M. Schmid, "Muscular Coactivation to Evaluate the Ergonomic Impact of Human-Robot Collaboration in Manual Handling Tasks", 2025 47th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)
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- G. Corvini, A. de Nobile, S. Ranaldi, T. Del Grossi, E. Ambrosini, C. De Marchis, and M. Schmid "EMG- Based Prediction of Target Location During Upper-Limb Reaching Movements: Impact of

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- G. Corvini, A. Ajoudani, S. Conforto, S. Ranaldi, M. Schmid, A. de Nobile, and D. Bibbo, "Assessing biomechanical risks in human-robot collaboration: Analysis of muscle activity with different intervention conditions", Gait & Posture (2023)
- A. de Nobile, I. Borghi, P. De Pasquale, D. Berger, A. Maselli, D. Bibbo, S. Conforto, F. Lacquaniti, G. Koch, A. D'Avella, and M. Russo, "Anticipatory responses characterize the Alzheimer's Disease continuum in a reaching task", Gait & Posture (2023)
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