Rendering Realistic Weight Sensations in Virtual Reality with Personalized Electrical Muscle Stimulation

Darstellung realistischer Gewichtsempfindungen in der Virtuellen Realität mittels personalisierter Elektrischer Muskelstimulation

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Abstract

Deep immersion in virtual reality (VR) and augmented reality (AR) is limited by the absence of convincing haptic feedback, particularly the sensation of weight. While Electrical Muscle Stimulation (EMS) offers a promising solution, a systematic framework for its effective and personalized application is lacking. This thesis addresses this gap through a multi-study investigation to develop and validate methods for rendering realistic weight sensations using personalized EMS within VR.

A foundational study (N=75) demonstrated that a dual-muscle EMS strategy is significantly superior to single-muscle approaches for perception and realism, establishing the benefit of synergistic muscle actuation. A second study (N=35) then systematically examined moderating factors, revealing that ergonomic parameters, such as a 90° elbow angle, are critical for realism. This study also identified a perceptual optimum for weight augmentation (+2 kg) and confirmed that individual user characteristics (e.g., age, BMI) significantly influence perceived realism, indicating that "one-size-fits-all" approaches are inadequate. Finally, a third study (N=36) indicated that for greater realism, EMS-based haptic feedback should be congruently synchronized with visual cues, as incongruent stimuli were found to create a significant sense of mismatch.

To address the need for personalization, machine learning models were developed using data from the first study. These models achieved F1-scores of up to 77% in predicting perceived weight differences based on key features including applied EMS amplitude, user thresholds, and BMI.

In synthesis, this thesis presents a multi-tiered framework for the optimization and personalization of EMS-based weight rendering. By identifying the effectiveness of synergistic muscle actuation, quantifying ergonomic and individual factors, defining the principles of visuohaptic congruence, and developing data-driven models for personalization, this work establishes design guidelines for immersive VR/AR systems. While these findings are bounded by factors such as the specific muscle groups and quasi-static holding tasks investigated, the developed methodology provides a validated basis for adapting haptic feedback to individual user characteristics.

Zusammenfassung

Tiefe Immersion in Virtueller Realität (VR) und Erweiterter Realität (AR) wird durch das Fehlen überzeugender haptischer Rückmeldungen, insbesondere der Gewichtswahrnehmung, eingeschränkt. Obwohl Elektrische Muskelstimulation (EMS) eine vielversprechende Lösung darstellt, fehlt es an einem systematischen Rahmen für ihre effektive und personalisierte Anwendung. Diese Dissertation schließt diese Lücke durch eine mehrstufige Untersuchung, um Methoden zur Darstellung realistischer Gewichtsempfindungen mittels personalisierter EMS innerhalb der VR zu entwickeln und zu validieren.

Eine Grundlagenstudie (N=75) wies nach, dass eine Zwei-Muskel-EMS-Strategie einer Ein-Muskel-Strategie hinsichtlich Wahrnehmung und Realismus signifikant überlegen ist. Dies belegt den Vorteil synergistischer Muskelaktivierung. Eine zweite Studie (N=35) untersuchte moderierende Faktoren und zeigte, dass ergonomische Parameter wie ein 90°-Ellbogenwinkel entscheidend für den Realismus sind. Zudem wurde ein Wahrnehmungsoptimum für die Gewichtserhöhung (+2 kg) identifiziert und bestätigt, dass individuelle Nutzermerkmale (z.B. Alter, BMI) den wahrgenommenen Realismus maßgeblich beeinflussen, was gegen "One-size-fits-all"-Ansätze spricht. Eine dritte Studie (N=36) deutete darauf hin, dass für einen höheren Realismus die EMS-basierte haptische Rückmeldung kongruent mit visuellen Reizen synchronisiert sein sollte, da inkongruente Stimuli ein deutliches Gefühl der Diskrepanz erzeugen.

Um die notwendige Personalisierung zu ermöglichen, wurden Machine-Learning-Modelle auf Basis der Daten der ersten Studie entwickelt. Diese erreichten F1-Scores von bis zu 77% bei der Vorhersage wahrgenommener Gewichtsunterschiede, basierend auf Merkmalen wie applizierter EMS-Amplitude, Nutzerschwellenwerten und BMI.

Zusammenfassend präsentiert diese Dissertation einen mehrstufigen Rahmen zur Optimierung und Personalisierung der EMS-basierten Gewichtsdarstellung. Durch die Identifizierung der Wirksamkeit synergistischer Muskelaktivierung, die Quantifizierung ergonomischer und individueller Faktoren, die Definition der Prinzipien visuohaptischer Kongruenz sowie die Entwicklung datengesteuerter Personalisierungsmodelle etabliert diese Arbeit Gestaltungsrichtlinien für immersive VR/AR-Systeme. Während diese Ergebnisse durch Faktoren wie die untersuchten spezifischen Muskelgruppen und quasi-statischen Halteaufgaben begrenzt sind, liefert die entwickelte Methodik eine validierte Grundlage für die Anpassung haptischen Feedbacks an individuelle Nutzermerkmale.

List of Prior Publications

This thesis is based on the following publications. The respective chapters in which these works are presented are noted in parentheses.

Vrontos, A., Nitsch, V., & Brandl, C. (2024). Electrical Muscle Stimulation for Kinesthetic Feedback in AR/VR: A Systematic Literature Review. *Multimodal Technologies and Interaction, 8*(2), 7. https://doi.org/10.3390/mti8020007 (Presented in Chapter 3)

Vrontos, A., Zolnouri, R., Mertens, A., Nitsch, V., & Brandl, C. (2025). Haptic Feedback for Interactive AR/VR Systems: Comparing Single- vs. Dual-Muscle EMS for Weight Perception. *Virtual Reality*. https://doi.org/10.1007/s10055-025-01204-2 (Presented in Chapter 5, Part A)

Vrontos, A., Zolnouri, R., Nitsch, V., Mertens, A., & Brandl, C. (2025). Personalized Electrical Muscle Stimulation for Precise Weight Perception in Virtual Reality: A Machine Learning Approach. In *2025 IEEE International Conference on Systems, Man, and Cybernetics*. Vienna, Austria. https://doi.org/10.1109/SMC58881.2025.11343549 (Presented in Chapter 5, Part B)

Vrontos, A., Nitsch, V., Mertens, A., & Brandl, C. (2026). Characterizing EMS-Induced Haptic Weight Perceptions: Effects of Posture, Augmentation Parameters, and User Variability. *IEEE Transactions on Haptics*. https://doi.org/10.1109/TOH.2026.3663216 (Presented in Chapter 6)

Vrontos, A., Lambert, S., Klasen, M., Sopka, S., Vogt, L., Mertens, A., & Brandl, C. (2025). Mixed Reality zum Anfassen: Innovation für virtuelle Haptik durch Gewichts- und Kraftsimulation. In J. Tröge, J. Sepczynski, H. Wiesner, & C. Runde (Hrsg.), *Virtuelle Beteiligung, reale Teilhabe: Digitale Technologien für eine inklusivere Gesellschaft*. Campus Verlag. https://doi.org/10.12907/978-3-593-46260-8 (Related concepts from this work are discussed in Chapter 8)

Statement on the Use of Artificial Intelligence

In accordance with the *Promotionsordnung der Fakultät für Maschinenwesen der Rheinisch-Westfälischen Technischen Hochschule Aachen* and the *Guidelines for Safeguarding Good Research Practice (Code of Conduct)* of the Deutsche Forschungsgemeinschaft (DFG), the author declares the use of the generative AI model Gemini (Google) as a supportive tool during the preparation of this thesis.

The application of this technology was strictly limited to technical and linguistic assistance, specifically:

- **Linguistic Refinement:** Improving grammar, clarity, and stylistic flow of the text.
- **Coding Assistance:** Support with syntax debugging and generating comments for code documentation.
- **LaTeX Support:** Assistance with formatting tables and resolving compilation errors.

Declaration of Scientific Independence:
The author affirms that this thesis constitutes an independent scientific achievement in accordance with the faculty's doctoral regulations. All research questions, experimental designs, primary data collection, and the intellectual interpretation of all results were conducted solely by the author. The AI tool was utilized exclusively as a technical assistant; no AI was used to generate original scientific insights, interpret findings, or perform the original intellectual synthesis and critical evaluation of existing research. The final version of all AI-assisted content was reviewed and verified by the author, who remains solely responsible for the work.

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Glossary

ANOVA Analysis of Variance. A statistical method used to compare the means of two or more groups.

AR Augmented Reality.

BMI Body Mass Index. A measure of body fat based on height and weight.

C/D Ratio Control-Display Ratio. The ratio between the movement of a controller and the corresponding movement in a virtual environment.

EEG Electroencephalography.

EMG Electromyography. A technique for evaluating and recording the electrical activity produced by skeletal muscles.

EMS Electrical Muscle Stimulation.

FES Functional Electrical Stimulation. A subset of EMS used to assist or restore voluntary motor functions.

GTO Golgi Tendon Organ. A proprioceptive sensory receptor that senses changes in muscle tension.

HCI Human-Computer Interaction.

IPQ Igroup Presence Questionnaire. A standardized questionnaire used to measure the sense of presence in virtual environments.

JND Just Noticeable Difference. The smallest amount of change in a stimulus that a person can detect.

ML Machine Learning.

MPs Motor Points. The locations on the skin where a muscle can be activated with the least amount of electrical current.

MT Motor Threshold. The minimum EMS intensity at which a visible muscle twitch is observed.

MWI Material-Weight Illusion. The perceptual illusion where objects that look or feel denser are perceived as heavier.

PRISMA Preferred Reporting Items for Systematic Reviews and Meta-Analyses.

PSE Point of Subjective Equality. The point at which two stimuli are perceived as identical.

PT Pain Threshold. The maximum EMS intensity that a participant reports as being comfortable and not painful.

ST Sensory Threshold. The minimum EMS intensity at which a participant first reports any sensation.

SVC Support Vector Classification. A type of machine learning algorithm used for classification tasks.

SWI Size-Weight Illusion. The perceptual illusion where larger objects are perceived as lighter than smaller objects of the same mass.

TENS Transcutaneous Electrical Nerve Stimulation. A subset of electrical stimulation used primarily for pain relief.

TES Tendon Electrical Stimulation. A technique that stimulates the tendon region to elicit a proprioceptive illusion of motion or force.

UCD User-Centered Design.

VR Virtual Reality.

XGBoost Extreme Gradient Boosting. A machine learning algorithm based on gradient boosted decision trees.

XR Extended Reality. An umbrella term that encompasses virtual reality (VR), augmented reality (AR), and mixed reality (MR).

1 Introduction

1.1 Motivation and Problem Statement

The continued evolution of virtual and augmented reality (VR/AR) promises to fundamentally alter human interaction with digital information, with transformative potential in fields ranging from surgical training and physiotherapy to industrial design and interactive entertainment. A defining characteristic of these immersive technologies hinges on their ability to generate a convincing sense of presence—the subjective, psychological sensation of truly "being there" in a virtual environment (Slater et al., 1994). While modern systems excel at delivering high-fidelity visual and auditory stimuli, a persistent challenge remains in replicating the physical sensations of the real world. Haptic feedback, which encompasses the sense of touch and force, is therefore widely recognized as a crucial component for building realistic, intuitive, and effective virtual experiences (Ramsamy et al., 2006; Speicher et al., 2019). Studies consistently show that haptic feedback is at least as important as visual information for fostering presence, with higher-fidelity systems yielding greater immersion, engagement, and even a stronger sense of virtual embodiment (Gibbs et al., 2022; Insko, 2001; Oakley et al., 2001; Richard et al., 2021; Sallnäs, 2010; Slater, 2002). Without the ability to feel the weight, resistance, and texture of virtual objects, the illusion of presence is fragile, and user interactions remain inefficient and unnatural.

This thesis is concerned with proprioceptive feedback, the branch of haptics responsible for our perception of body position, movement, and force. It is the sense that allows us to feel the weight of an object in our hand or the resistance of a closing door. This modality is paramount for tasks involving object manipulation and physical exertion. Traditionally, rendering these forces has required complex and often cumbersome mechanical systems. Solutions such as grounded exoskeletons, cable-driven robots, or pneumatic devices, while capable of generating powerful forces, suffer from significant practical drawbacks: they are typically bulky, expensive, restrictive, and require a large operational footprint (Lim et al., 2021). Their cumbersome nature not only limits portability and scalability but also physically tethers the user, constraining natural movement

and hindering the very immersion they are meant to create. This fundamental limitation has motivated the search for more accessible, wearable, and scalable haptic technologies.

Electrical Muscle Stimulation (EMS) has emerged as a powerful and promising alternative. As a lightweight, wearable, and cost-effective technology, EMS circumvents the need for external mechanical actuators by co-opting the body's own muscles to generate force sensations (Vrontos et al., 2024). Pioneering research, dating back to 2006, established that by delivering controlled electrical pulses to targeted muscle groups, it is possible to induce contractions that are synchronized with haptic events in a virtual world (Kruijff et al., 2006). This approach is remarkably versatile, having been used to simulate a range of haptic experiences from the impact of virtual objects to the resistance of solid walls (Lopes et al., 2017). The growing research activity surrounding EMS for haptic applications from that period onward, reflected in the increasing number of publications in curated databases (see Figure 1.1), underscores its perceived potential. The research presented in this thesis was conducted within the scope of the 'interaktionsKRAFT' project, funded by the German Federal Ministry of Research, Technology and Space (BMFTR), which aimed to explore precisely these kinds of innovative haptic technologies for immersive interaction (Vrontos, Brunner, et al., 2025).

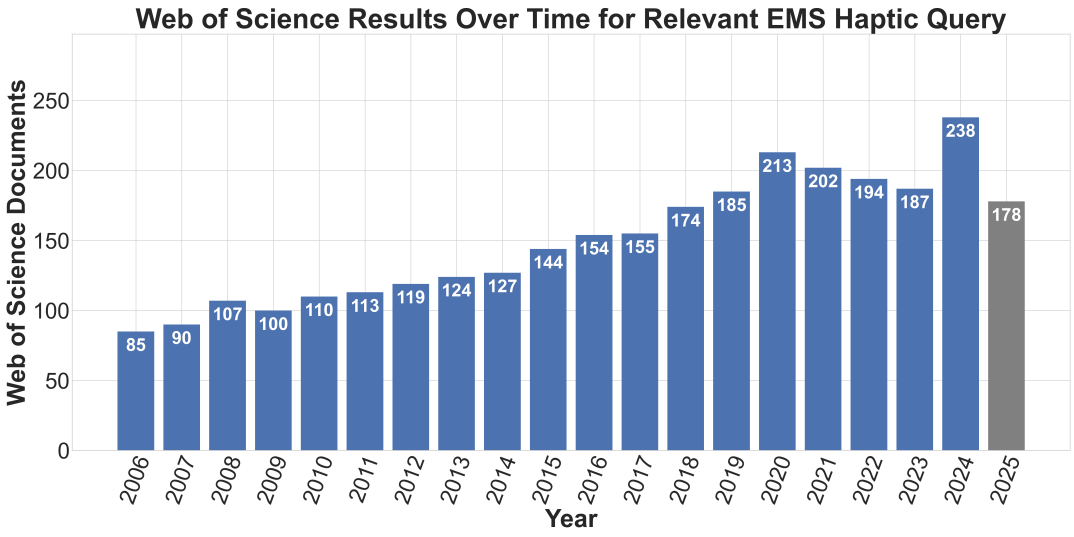


Figure 1.1: Number of Web of Science documents (Articles, Proceeding Papers, Early Access) per year (2006-2025) resulting from the search query used in the systematic literature review Vrontos et al. (2024). Data collected November 2025; the final year represents partial data.

The application of EMS for rendering weight is particularly effective, as it directly taps into the physiological basis of heaviness perception. Humans primarily judge an object's weight through the sense of effort, a key component of proprioception derived from the motor commands sent to our muscles and the resulting muscular activation (Jones, 1986; Proske & Gandevia, 2012; Toma & Lacquaniti, 2016). By stimulating the antagonist muscles—those that oppose a voluntary action, such as stimulating the triceps while the user holds an object with their biceps—the system can create a tangible sensation of resistance. The user must exert more physical effort to counteract this artificially induced force, leading to a compelling and realistic perception of increased weight (Faltaous et al., 2022; Galofaro et al., 2022; Lopes et al., 2018).

However, despite its considerable potential and the effectiveness of early feasibility studies, the translation of EMS from a novel concept to a robust and reliable haptic modality is far from complete. The user's perception of EMS is highly complex, influenced not only by the direct EMS parameters but also by their posture, their unique physical characteristics, and even their expectations. Key challenges remain, such as the inverted muscle recruitment pattern of EMS which can lead to rapid fatigue, and its poor muscle selectivity which can make sensations feel unnatural (Diamant & Reilly, 2011; Gregory & Bickel, 2005). The core problem this thesis confronts is the lack of a systematic and user-centric framework for rendering realistic weight sensations using EMS. Without a deeper, evidence-based understanding of how to manage EMS strategies, account for ergonomic factors, personalize feedback for individual users, and coherently integrate that feedback with the dominant visual information in VR, EMS-based haptics will fail to reach its full potential, remaining an academic curiosity rather than a transformative tool for immersive interaction.

1.2 Research Gap and Objectives

The field of haptics offers a diverse array of interfaces for rendering force, ranging from wearable solutions like exoskeletons (Zhang et al., 2019) and pulley systems (Akahane et al., 2013) to external robotic systems and even non-contact approaches utilizing airborne ultrasound (Fan et al., 2022; Hoshi et al., 2010; Raza et al., 2020). However, as a comprehensive survey by Lim et al. (2021) details, a significant drawback of many of these conventional approaches is that their bulky size, high cost, and restrictive nature limit their feasibility for broader application. Furthermore, non-contact methods have not yet achieved the reliability or precision of their mechanical counterparts (Rakkolainen et al., 2020). In comparison, EMS presents a compelling path forward, offering the advantages

of a smaller physical footprint and greater energy efficiency (Yem & Kajimoto, 2017). Because EMS stands out as such a promising and practical technology, it is critical to address the specific gaps in the knowledge that currently prevent its full potential from being realized.

A thorough review of the existing EMS literature reveals several critical, interconnected gaps that currently prevent the widespread adoption and effectiveness of EMS for realistic weight rendering. Foundational studies have demonstrated that EMS can influence perceived weight, but they have also highlighted key unanswered questions regarding the quality, context, and personalization of the experience. The scientific work reported in this thesis aims to systematically address these specific research gaps.

The first major gap is the lack of a systematic, quantitative comparison between different EMS strategies, with a specific focus on perceptual realism. Much of the prior work has focused on single-antagonist EMS (e.g., activating only the triceps brachii to make an object feel heavier) (Faltaous et al., 2022). While effective at generating a sensation of force, this approach has been qualitatively criticized by participants in foundational studies as feeling unnatural, with feedback suggesting that stimulating multiple muscle channels would be more realistic (Galofaro et al., 2022). This aligns with the understanding that humans perceive force through the coordinated activity of many muscles (Toma & Lacquaniti, 2016). Yet, a systematic comparison of single-muscle versus multi-muscle EMS for weight perception—one that explicitly measures perceived realism alongside magnitude—has not been sufficiently addressed.

The second gap is the absence of a robust, data-driven methodology for personalizing EMS feedback to account for high inter-subject variability. Users differ vastly in their physiology, including their individual sensitivity to EMS, as well as their demographic and physical characteristics (e.g., age, BMI, strength). These differences mean that a single, predefined EMS intensity is functionally useless in a practical application; an intensity that is perfect for one user may be imperceptible to another and uncomfortable for a third. While the need for personalization is acknowledged (Lopes et al., 2017), and machine learning (ML) has been proposed as a solution (Ghosn, 2023), a model that predicts the specific EMS amplitude needed to achieve a target weight perception based on a user's unique profile has not yet been developed.

The third gap is the limited understanding of how ergonomic and contextual factors influence the effectiveness and perceived realism of EMS-induced weight sensations. User posture, such as the angle of the elbow joint, fundamentally alters the biomechanics of the arm, yet its impact on EMS perception remains unexplored. Similarly, it is unclear how the characteristics of the weight augmentation itself, such as its magnitude (a small vs. large increase) or the base weight from which it starts, affect the user's

sense of realism. Identifying which postures and weight combinations produce the most realistic sensations is critical for designing effective and ergonomic haptic systems, but this foundational knowledge is currently missing.

Finally, even a perfectly personalized haptic sensation does not exist in a vacuum. In VR and AR, haptic feedback is presented alongside powerful, often dominant, visual information. A critical and underexplored gap exists in understanding the principles of multisensory integration for EMS-based weight rendering. It is unclear how users perceive and react to congruent versus incongruent visuohaptic stimuli, and how sensory conflicts might impact the very sense of realism and presence that the haptics are meant to enhance.

To address these distinct but related gaps, this thesis pursues five primary objectives:

O1: To systematically compare the perceived magnitude and, crucially, the perceived realism of single-muscle versus dual-muscle EMS for augmenting the sensation of a held weight.

O2: To develop and validate data-driven ML models that personalize EMS feedback by leveraging individual user characteristics (demographic, physical, and sensory) to predict the EMS amplitude required to achieve a precise target weight perception.

O3: To characterize the influence of key ergonomic and task-related factors—specifically user posture (elbow angle) and the parameters of the weight augmentation—on the perceived realism and required intensity of EMS.

O4: To investigate the principles of multisensory integration by systematically comparing the effects of congruent and incongruent visuohaptic feedback on user perception (realism, presence, mismatch) and motor behavior.

O5: To synthesize the findings from these empirical investigations into a comprehensive, evidence-based framework that provides practical guidelines for designing and implementing personalized, realistic, and effective EMS-based weight rendering systems in virtual reality (VR).

By achieving these objectives, this thesis aims to move the field beyond foundational feasibility studies and provide the systematic, user-centric understanding necessary to unlock the full potential of EMS as a transformative haptic technology.

1.3 Thesis Outline

This thesis is organized into nine chapters, following a logical progression from foundational theory to empirical investigation, and culminating in a synthesis of the findings. This structure is designed to build a comprehensive argument for a systematic, user-centric approach to rendering weight sensations with EMS.

Chapter 1 serves as the introduction, establishing the motivation, problem statement, and core objectives of the research. It situates the work within the broader context of haptics for immersive virtual environments and defines the specific research gaps this thesis aims to address, thereby providing a clear roadmap for the chapters that follow.

Chapter 2 provides the necessary theoretical background. This chapter synthesizes knowledge from several domains, reviewing the principles of haptic feedback, the physiological mechanisms of proprioception, and the psychophysics of human weight and force perception. It then delves into the specific technical and physiological principles of EMS, including its parameters, advantages, and known challenges, such as unnatural muscle recruitment patterns and fatigue. Finally, it establishes the importance of personalization in human-computer interaction (HCI) and adaptive haptic systems.

Chapter 3 presents a systematic review of the state of the art in EMS for kinesthetic feedback, based on the author's published work. This chapter outlines the review methodology and presents a synthesis of findings from the existing literature, cataloging applications, common parameters, and evaluation measures. Crucially, it provides the evidence to formally substantiate the research gaps identified in Chapter 1, thereby justifying the novel contributions of the subsequent empirical work.

Chapter 4 details the overarching research methodology that unifies the empirical studies. It describes the quantitative, within-subjects experimental paradigm, the standardized procedures for participant recruitment and ethical considerations, and the specific EMS hardware, software, and safety protocols used consistently throughout the research. Furthermore, it outlines the common data collection methods, such as weight-matching tasks and psychophysical procedures like the Method of Adjustment for determining the Point of Subjective Equality (PSE), and the primary data analysis techniques, including statistical tests and the ML models employed for personalization.

The empirical core of this thesis is presented in **Chapters 5, 6, and 7**. Each chapter details a distinct study designed to address the research objectives:

- **Chapter 5** directly addresses Objectives O1 and O2. It presents a foundational study that first provides a systematic, quantitative comparison of the efficacy and perceived realism of single- versus dual-muscle EMS. It then leverages the large

dataset from this experiment (N=75) to develop, train, and validate three ML models for personalizing EMS feedback based on user characteristics.

- **Chapter 6**, which targets Objective O3, proceeds to characterize the key contextual factors influencing EMS perception. It systematically investigates the effects of user posture (elbow angle), the magnitude of the weight augmentation, and the base weight on both perceived realism and the required EMS intensity.
- **Chapter 7**, which targets Objective O4, concludes the empirical section by exploring the interplay between different sensory modalities. It presents a systematic comparison of EMS-based haptic feedback against visual-only and congruent visuohaptic feedback to isolate its effects on user perception—specifically realism, presence, and sensory mismatch—and on objective motor behavior, as measured by kinematic jerk.

Chapter 8 provides a general discussion and synthesis of the findings, addressing Objective O5. This chapter moves beyond the results of the individual studies to connect the key findings into a cohesive whole. It proposes two key contributions: first, a comprehensive, evidence-based framework for designing personalized and realistic EMS-based weight feedback systems, and second, a methodological blueprint aimed at improving replicability in the field. The chapter also discusses the broader implications of this work for practical applications, critically reflects on its limitations, and proposes promising directions for future work.

Finally, **Chapter 9** offers a concise conclusion to the thesis. It summarizes the primary scientific contributions and offers final remarks on the future trajectory of EMS as a practical and transformative haptic technology.

2 Theoretical Framework & Background

2.1 Haptic Feedback in AR/VR

2.1.1 Principles and Types of Haptic Feedback

Haptic feedback encompasses both cutaneous feedback, which relates to sensations on the skin such as texture and temperature, and proprioceptive feedback, which pertains to forces and the user's body position (Saddik et al., 2011). In essence, a haptic display functions as a bilateral communication interface between the human user and the computer system. By allowing users to perceive the physical properties of virtual objects through the sense of touch, it provides a crucial layer of sensory information that complements traditional visual and auditory cues, thereby greatly enhancing immersion (D. Wang et al., 2019).

Haptic feedback systems can be broadly categorized based on the nature of user interaction. A key distinction is made between passive haptic feedback, which is preprogrammed and does not change based on user input, and active haptic feedback, which dynamically responds to a user's movements and actions within the virtual environment (Gao & Spence, 2025). This active, responsive feedback is particularly vital for creating convincing and interactive virtual experiences where users can manipulate objects and feel the consequences of their actions in real-time.

2.1.2 Enhancing Immersion, Presence, and User Experience

Haptic feedback is widely recognized as a crucial component for building immersive and intuitive experiences in both VR and AR (Ramsamy et al., 2006; Speicher et al., 2019). While modern systems excel at delivering high-fidelity visual and auditory information, a persistent challenge in achieving deep immersion is the difficulty of replicating physical sensations, which are fundamental to fostering a genuine sense of presence (Ramsamy

et al., 2006; Speicher et al., 2019; D. Wang et al., 2019). Integrating haptics with visual and auditory modalities addresses this gap, providing multisensory cues that mimic real-world interactions and significantly improve user immersion, presence, and task performance (Marchal & Pacchierotti, 2025).

To understand the impact of haptics, it's essential to distinguish between the key concepts of immersion and presence. Immersion is best described as an objective measure of a system's technological capability to deliver a convincing and all-encompassing sensory experience (Gao & Spence, 2025). It is a graded experience of involvement that can progress through levels of engagement, engrossment, and total immersion, often characterized by a loss of awareness of time and the physical world (Jennett et al., 2008).

Presence, in contrast, is the user's subjective psychological sensation of "being there" in the virtual environment, even when physically situated elsewhere (Gao & Spence, 2025; Slater et al., 1994; Witmer & Singer, 1998). This psychological state is contingent on the user's attention shifting from the physical world to the virtual one (Witmer & Singer, 1998). While related, the two concepts are distinct; a user can be deeply immersed in an abstract task, such as playing Tetris, without feeling a sense of presence in a tangible virtual world (Jennett et al., 2008). The experience of presence is theorized to depend on two conditions: involvement, which is the selective focusing of attention, and the level of immersion provided by the system, which enables the user to perceive themselves as enveloped by and interacting with the virtual environment (Witmer & Singer, 1998).

The literature strongly supports the role of haptic feedback as being at least as significant as visual information for creating a convincing sense of presence; in some scenarios, haptics are considered even more crucial (Gibbs et al., 2022). Research has demonstrated that presence is significantly increased through the use of both active haptic feedback (Oakley et al., 2001; Slater, 2002) and passive haptics (Insko, 2001). Both forms are instrumental in enhancing the overall user experience by cultivating a greater sense of engagement, a more profound feeling of virtual embodiment, and even an improved sense of social presence—defined as the "sense of being with another" (Biocca et al., 2003)—in interactive scenarios (Insko, 2001; Oakley et al., 2001; Richard et al., 2021; Sallnäs, 2010; Slater, 2002). This effect is further amplified when feedback is expanded beyond the hands; Söderström et al. (2022) found that delivering vibrotactile feedback to the upper body via a vest in First-Person Shooter games enhanced players' spatial awareness and perceived realism, thereby creating a deeper sense of immersion than controller-based feedback alone.

This principle extends to both VR and AR, where haptics are critical for enhancing

what is termed "Object Presence"—the subjective feeling that a virtual object truly exists within the user's real-world environment. Overcoming the technological challenge of making virtual objects feel tangible is highly dependent on the effective integration of multi-sensory feedback, with haptics playing a primary role (Kang & Lee, 2018). However, the perceived realism of this feedback is fundamentally limited by the mathematical rendering method. Lorenz et al. (2023) demonstrated that for high-force rigid interactions (e.g., steel-on-steel), standard "penalty-based" algorithms were consistently rated as the least realistic, as they model hardness merely as a stiff spring. In contrast, alternative algorithms that enforced non-penetration (impulse-based, constraint-based, and rigid-body methods) achieved significantly higher realism ratings, highlighting that a convincing physical interaction requires algorithmic fidelity that matches the user's material expectations.

2.1.3 Current Challenges and the Emergence of EMS

Despite the recognized importance of haptics, significant challenges hinder the widespread implementation of realistic tactile and proprioceptive feedback in VR/AR. General obstacles include the high cost, limited portability, and potential safety issues of traditional grounded systems, which can suffer from instabilities due to system delays or unexpected contacts (Marchal & Pacchierotti, 2025; D. Wang et al., 2019). Psychologically, a critical challenge is the risk of misinterpretation; if a haptic sensation is ambiguous or poorly rendered, it can break the user's immersion by drawing their attention to their own body rather than the virtual interaction (Gao & Spence, 2025).

These challenges are particularly acute in the domain of weight perception. While weight can be simulated through various methods—including direct proprioceptive feedback, pseudo-haptic visual illusions, and indirect tactile feedback—a major hurdle remains in achieving the same level of perceptual precision as with real objects. This involves simulating weight changes at the very threshold of human perception, a limit known as the Just Noticeable Difference (JND)—the smallest change a person can reliably detect (Lim et al., 2021). Furthermore, rendering the sensation of heavyweight objects using ungrounded, wearable devices poses a formidable technical problem (Lim et al., 2021).

In response to the limitations of mechanical systems, EMS has emerged as a promising wearable alternative. This approach was pioneered by researchers such as Kruijff et al. (2006), who proposed that EMS could induce muscle contractions synchronized with virtual haptic events. As the systematic literature review conducted for this thesis has shown, research interest in this domain has surged over the past decade (Vrontos et al.,

2024).

Pioneering work by Lopes et al. (2017) and Lopes et al. (2018) demonstrated a mobile system that used EMS to generate force sensations in the shoulder, arm, and wrist, effectively simulating physical properties like weight and resistance in various scenarios. They showed that dynamically adjusting parameters like pulse amplitude and width could correspond to lifting virtual objects of varying weights and that EMS systems represent a practical, lightweight, and scalable solution for proprioceptive feedback. However, a key limitation of this foundational work was the lack of a quantitative relationship between the EMS parameters and the resulting perceived sensation; the feedback was primarily binary, distinguishing only between "force present" and "no force."

Subsequent foundational work focused on the specific application of weight perception. Research by Faltaous et al. (2022) demonstrated the feasibility of manipulating perceived weight by stimulating antagonist muscles, showing that activating the triceps while a user held an object with their biceps significantly increased the object's perceived heaviness. Their work confirmed that users had to exert more effort to overcome the artificially induced contraction, convincingly simulating an increased load. Similarly, Galofaro et al. (2022) developed a mobile system with user-specific calibration for rendering weight. However, their approach was limited to stimulating a single muscle with predefined parameters. This is a significant constraint, as the optimal EMS parameters are highly dependent on numerous muscle- and user-specific factors. The calibration method itself also required external force sensors and length measurements, which reduces the system's mobility and ease of use.

These limitations highlight a clear gap in the literature: the need for a more flexible, multi-muscle, and sensor-free approach to calibration and EMS that can create a precise, quantitative link between EMS parameters and a user's subjective perception. The scientific work reported in this thesis aimed at addressing these research gaps directly.

2.2 Human Perception of Weight and Force

2.2.1 Sensory Receptors and Channels

As categorized by See et al. (2022), human haptic perception is mediated by two primary and distinct information channels: the tactile (or cutaneous) system and the proprioceptive (or kinesthetic) system. Tactile feedback originates from contact with the skin and is responsible for sensations such as pressure, vibration, texture, and temperature (Jones, 2009; Saddik et al., 2011). In contrast, proprioceptive feedback provides information

about the body itself, enabling the perception of weight, compliance, and the position, motion, and forces of the limbs (Jones, 1997; Saddik et al., 2011). The entire haptic system relies on a diverse array of mechanoreceptors located within the skin, muscles, and joints that transduce physical stimuli into neural signals (Purves et al., 2004).

The tactile sense is facilitated by four main types of mechanoreceptors embedded in the skin, each specialized for different stimuli: Meissner's corpuscles detect light touch, Pacinian corpuscles sense high-frequency vibration, Merkel disks respond to steady pressure, and Ruffini endings detect skin stretch (Saddik et al., 2011). Figure 2.1 provides a visual depiction of these receptors and also includes the Krause end bulb, a structure generally considered to be a thermoreceptor for sensing cold (Clark et al., 2018).

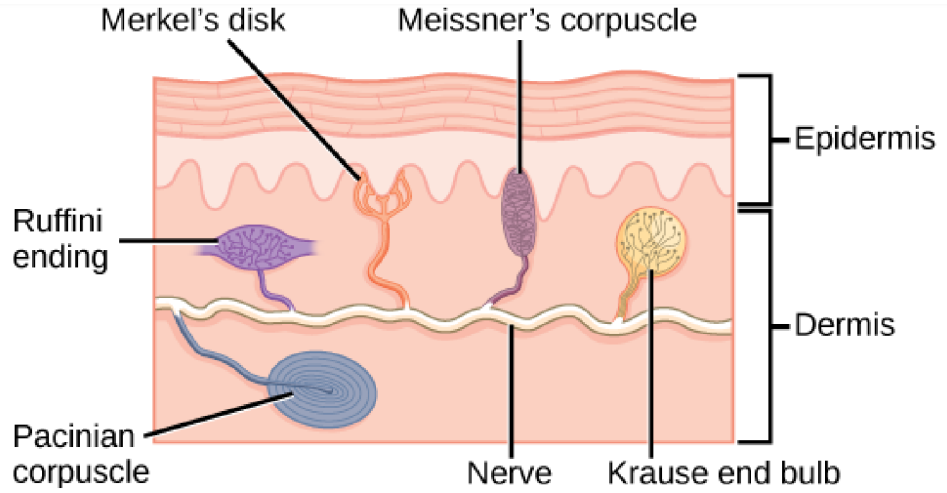


Figure 2.1: The four primary types of mechanoreceptors found in human skin and the Krause end bulb, which is thought to be a thermoreceptor. Reprinted from Clark et al. (2018), licensed under CC BY 4.0.

The kinesthetic system underpins proprioception, a multifaceted sense encompassing not only the perception of joint position and movement but also the senses of force, muscle tension, weight, and even the size of manipulated objects (Horváth et al., 2023; Jones, 1997). This sense is now commonly understood to encompass two submodalities: joint position sense (the awareness of a static limb position) and kinesthesia (the conscious awareness of joint motion) (Han et al., 2016). Proprioceptive feedback is generated by specialized receptors, most notably the muscle spindles, which monitor the length and rate of change in length of muscles, and the Golgi tendon organs (GTOs), which monitor muscle tension (Kaya et al., 2018; Purves et al., 2004). While other receptors in the

skin and joints contribute, contemporary understanding suggests that muscle spindles are the primary sensors for kinesthesia, with joint receptors thought to act mainly as limit detectors for the range of motion (Proske & Gandevia, 2012). While the terms "kinesthetic" and "proprioceptive" are often used interchangeably in HCI literature, this thesis will, for the sake of precision, use "proprioceptive feedback" as the primary term, as it more broadly encompasses the sensations of force, weight, and static body position central to this research.

Ultimately, proprioception is best understood as an integrated process combining peripheral "hardware"—the raw sensory signals from these various mechanoreceptors—with central "software". This "software" refers to the brain's complex ability to organize, interpret, and integrate the incoming signals to form a coherent perception of body position and movement (Han et al., 2016).

2.2.2 The Role of Effort in Perception

The human judgment of an object's heaviness relies primarily on the sense of effort (Jones, 1986). This sense is a key component of proprioception that originates not from incoming sensory signals, but from the outgoing motor commands sent to the muscles and the resulting muscular activation (Proske & Gandevia, 2012). A prevailing theory posits that sensations of force and heaviness are derived mainly from these centrally generated motor commands rather than being signaled directly by peripheral sensory receptors (afferents) (Jones, 1986). Accompanying these outgoing commands is an internal signal, often termed an efference copy, which is essentially a duplicate of the motor command sent to the brain's own sensory areas to allow it to anticipate the sensory consequences of the movement. While active, voluntary movements engage both this efferent motor command and afferent sensory feedback, passive movements rely almost exclusively on afferent signals alone (Horváth et al., 2023). Specifically, the pure sense of effort is thought to be generated by the central motor command, while the more integrated perceptions of force and heaviness arise from a combination of this central signal and peripheral feedback from receptors like the GTOs, which signal muscle tension (Proske & Gandevia, 2012).

Strong evidence supports the central role of motor commands in perception. For instance, in experiments involving muscle fatigue or partial paralysis, a greater motor command is required to produce a given force. In these conditions, subjects consistently overestimate the force or weight, indicating that their perception is tightly coupled to the magnitude of the outgoing command (Jones, 1986).

This link is further quantified by research using electromyography (EMG) to measure

muscle activity. Foundational work by Toma and Lacquaniti (2016) established that approximately 60% of the variance in perceived force could be directly explained by the global electrical activity of eight key arm muscles. This relationship between muscular effort and perceived heaviness was later confirmed to be largely linear Mangalam, Conners, and Singh (2019). This near-linear relationship is particularly noteworthy because the psychophysical experience of most sensory stimuli is nonlinear, typically following a power law (J. Kim et al., 2022; Stevens, 1957, 1970). This suggests that the neural encoding of muscular effort may be distinct from other sensory modalities. Importantly, this predictive power is specific to force and weight; research confirms that muscular effort is not a predictor for the object's perceived length (Mangalam, Conners, Kelty-Stephen, & Singh, 2019).

2.2.3 Psychophysical Laws and Models

The brain's interpretation of proprioceptive information is a complex process of integration. Rather than relying on signals from individual receptors, the brain processes a combined "population code"—an encoding scheme where information is represented by the joint activity of a large number of neurons—from afferent signals across multiple muscles. This ensemble signal is used to compute a holistic representation of the limb's endpoint in space, not just the angles of individual joints (Proske & Gandevia, 2012). This process of judging an object's weight can be conceptualized as occurring in three stages: a sensory stage for detecting physical properties, a perceptual stage where an internal representation is formed, and a decisional stage where that percept is transformed into a reportable judgment (Valdez & Amazeen, 2008).

The relationship between physical stimuli and subjective perception is often described by fundamental psychophysical principles. Weber's Law, for instance, explains our differential sensitivity to changes in stimuli, while Stevens' Power Law describes the nonlinear relationship between a physical stimulus's intensity (Φ) and its perceived magnitude (Ψ) (Kern, 2009; Stevens, 1970). This relationship is expressed as an exponential function, $\Psi = k\Phi^a$. For the perception of muscular force during a static contraction, the exponent (a) has been measured to be approximately 1.7. This value indicates a nonlinear, expansive relationship, where the perceived force grows disproportionately faster than the actual physical force exerted (Kern, 2009).

Modern theories of heaviness perception, such as the fusimotor reafference model, integrate both central motor commands (efference) and peripheral sensory feedback (afference). This model posits that the brain compares its outgoing motor command against the incoming sensory signal (reafference) from muscle spindles, whose sensitivity

is actively adjusted by the fusimotor system. In this view, signals from both GTOs and these pre-tuned muscle spindles contribute to the final sensation (Mangalam et al., 2021). Perception is also highly specific to the mechanical variables involved; for example, perceived heaviness is primarily a function of an object's static moment, whereas perceived length is a function of its moment of inertia (Mangalam et al., 2021). Further refining this, research by Waddell and Amazeen (2017) established that the perception of heaviness is determined by the ratio between muscle activity and lift acceleration, a principle that holds true across lifts involving the shoulder, elbow, or wrist.

However, these psychophysical principles can be context-dependent. In a whole-body load carriage task, for instance, the probability of detecting a weight difference was found to be lower for heavier reference weights, a finding that is inconsistent with Weber's law in that specific context (Chen et al., 2021). This highlights that while general laws provide a foundational model, the nuances of human perception are often shaped by the specific task and environment.

2.2.4 Illusions, Biases, and Memory Effects

Human perception of weight is not a direct readout of an object's physical mass but is subject to a variety of illusions, contextual biases, and memory effects. The most well-known of these is the Size-Weight Illusion (SWI), in which a larger object is perceived as being lighter than a smaller object of the same mass (Jones, 1986). As a classic example of visuohaptic interaction, the mechanisms of this illusion are discussed in detail in Section 2.4.3.

Our perception is also heavily influenced by recent experience through a process known as sensorimotor memory. When lifting a series of objects, the brain uses implicit knowledge from recent lifts to predict the upcoming object's weight and pre-emptively scale fingertip forces accordingly (van Polanen & Davare, 2015). This predictive mechanism influences not only the motor plan but also the conscious perception of weight itself. This link creates a perceptual bias: for instance, a light object is perceived as feeling even lighter when it is lifted immediately after a heavy one, due to the mismatch between the planned force (based on the heavy object) and the actual force required (van Polanen & Davare, 2015). This form of kinaesthetic memory is notably stable; memory for an object's location, for example, shows no appreciable decay after 10 seconds, whereas visual memory for the same location decays rapidly, highlighting the robustness of the proprioceptive system for spatial tasks (Salvendy, 2012). However, for properties gathered through sequential exploration, the system relies on a more volatile haptic sensory memory—a tactile equivalent to iconic memory. Drewing and Lezkan

(2021) demonstrated that this memory system is responsible for integrating information across multiple exploratory movements to form a composite percept. Crucially, this integration is susceptible to disruption; the introduction of high-energy tactile patterns, or "masks", between sequential movements significantly reduces perceptual precision, indicating that haptic information preservation is a fragile process during the active accumulation of sensory data.

Other factors can also modulate weight perception. A critical factor is muscular fatigue, as it can cause a dissociation between a user's sense of effort and their perception of an object's actual heaviness (Burgess & Jones, 1997). As muscles fatigue, a greater central motor command is required to generate a given force, leading to a distinct increase in the perceived sense of effort. While the perceived heaviness of the object also tends to increase—an effect known as the "fatigue-weight illusion"—studies have shown that this increase is significantly smaller than the increase in perceived effort. This growing gap, or dissociation, between the two sensations is hypothesized to serve as a biological signal to inform an individual that their motor function is compromised (Burgess & Jones, 1997). Additionally, actively wielding an object increases its perceived heaviness compared to holding it statically, which suggests that the increased afferent signals from muscle spindles during movement contribute to the sensation (Mangalam et al., 2021).

2.2.5 Objective Measurement of Subjective Perception

Quantifying subjective internal states, such as proprioception or the feeling of immersion, presents a significant methodological challenge. To address this, researchers have developed various techniques to capture objective, measurable data that correlates with these subjective experiences.

In the domain of proprioception, acuity is commonly assessed using three main methods: the threshold to detection of passive motion (TTDPM), which measures sensitivity to movement; joint position reproduction (JPR), which tests the ability to replicate a limb's position; and active movement extent discrimination (AMEDA), which evaluates the capacity to distinguish between movements of different lengths (Han et al., 2016). However, it's crucial to recognize that proprioceptive accuracy is not a generalizable skill; it is highly site-specific and method-specific. An individual's performance on one test at a given joint does not typically correlate with their performance on a different test or at another joint, underscoring the need for carefully chosen and highly specific measurement protocols (Horváth et al., 2023). This joint-dependency is evident in the resolution of kinesthetic perception, where the JND for joint angle is approximately 2 degrees for the fingers and wrist but improves to around 1 degree for the more proximal

shoulder joint (Kaber & Zhang, 2011).

Given the complexities of direct measurement, an effective alternative is to analyze a user's motor behavior as a proxy for their internal perception. Research demonstrates that the kinematic features of a user's lifting motion are reliable objective indicators of the perceived weight of a virtual object. A heavier perceived weight directly shapes motor execution, resulting in objectively measurable changes such as lower peak velocity, longer movement duration, and a more symmetric velocity profile (Moosavi et al., 2024). Importantly, these kinematic alterations correlate strongly with subjective user reports, confirming that a perceptual illusion is powerful enough to affect both the motor control system and conscious awareness. For instance, studies show a direct link between these altered lifting kinematics and perceived fatigue as measured by a standardized tool like the Borg CR10 questionnaire (Moosavi et al., 2024).

This principle of identifying perceptual thresholds extends to other aspects of virtual and augmented environments. In AR, for example, the perceptual threshold for reliably detecting an increase in a virtual object's size (the JND) is approximately 5.18%, while the PSE—the point at which the changed object was perceived as identical to the reference—is 4.00% (L. Wang & Sandor, 2021). Ultimately, complex experiences like immersion are most effectively measured using a mixed-methods approach. This involves combining subjective self-reports from validated questionnaires with objective, quantitative data from behavioral or physiological measures, such as task performance times, kinematic analysis, or eye-tracking (Jennett et al., 2008).

2.3 Principles of EMS for Proprioceptive Feedback

The artificial generation of muscle tension via EMS is a recognized and effective indirect haptic technique for simulating physical properties like weight and resistance in virtual environments (Lim et al., 2021). The underlying principle, as demonstrated by Lopes et al. (2018), is the emulation of the body's own biomechanical and proprioceptive signals. By activating specific muscles—typically antagonist muscles—EMS can create a convincing sensation of holding a heavy object or encountering a resistive force where none physically exists.

2.3.1 Physiological Foundations

The fundamental advantage of EMS is its ability to induce muscle contractions by electrically stimulating motor nerves, bypassing the need for voluntary effort from the user.

This makes it a uniquely versatile tool, particularly for applications involving individuals who may have difficulty with voluntary muscle activation (Nishikawa et al., 2021).

When an electrical stimulus is applied to a peripheral nerve or muscle belly, it activates a mixed nerve, initiating a cascade of physiological events. This activation simultaneously generates two signals: an efferent (motor) volley that propagates down the nerve to the neuromuscular junction to cause a muscle contraction, and an afferent (sensory) volley that travels in the opposite direction up to the spinal cord and brain, providing sensory feedback (Milosevic et al., 2020). This process differs from voluntary activation in a key way. EMS causes a bidirectional signal propagation along motor axons; in addition to the standard orthodromic signal that causes the contraction, an antidromic signal travels backward toward the central nervous system. This antidromic signal is hypothesized to contribute to the neuroplastic effects sometimes observed with EMS training (Milosevic et al., 2020).

At the neural level, the underlying mechanism for this activation is the depolarization of voltage-gated sodium (Na^+) channels in the axon membrane, a process comprehensively described in the foundational work of Hodgkin and Huxley (Hodgkin & Huxley, 1952). For myelinated axons, this activation can be modeled by an "activating function", which demonstrates that depolarization is driven by the voltage gradient created by the external electric field between adjacent Nodes of Ranvier. This model explains a key principle of EMS: larger diameter axons, which have longer distances between their nodes, require a lower stimulus intensity to reach their activation threshold (Bhadra, 2015).

Once an action potential is triggered, it propagates across the muscle fiber membrane (sarcolemma), leading to the release of intracellular calcium ions (Ca^{2+}) from the sarcoplasmic reticulum. This influx of Ca^{2+} initiates the binding of actin and myosin filaments within the sarcomere, causing it to shorten and ultimately generate mechanical force (Bhadra, 2015).

2.3.2 Technical Parameters and Best Practices

The effectiveness, safety, and subjective comfort of EMS are governed by the precise configuration of several technical parameters. The fundamental characteristics of any EMS signal are its pulse form (waveform), intensity (amplitude and pulse width), and frequency, which are visually defined in Figure 2.2 (Doucet et al., 2012). Modern EMS systems are typically current-regulated, a crucial design choice that ensures a consistent and predictable amount of electrical charge is delivered to the target tissue, even as the impedance of the electrode-skin interface changes due to factors like sweat or movement

(Milosevic et al., 2020).

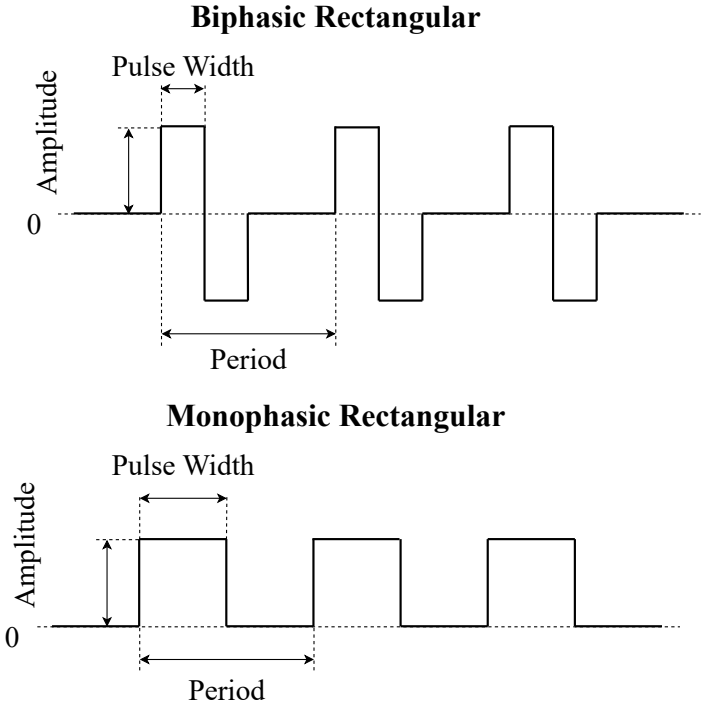


Figure 2.2: Comparison of two common pulse forms, biphasic and monophasic rectangular, illustrating the key parameters that define an EMS pulse: amplitude, pulse width, and frequency. Reprinted from Vrontos et al. (2024), licensed under CC BY 4.0.

The intensity of an EMS pulse is determined by the interplay between its amplitude (current level) and duration (pulse width). These two variables are inversely related, as described by the strength-duration curve; a longer pulse duration allows for a lower amplitude to achieve the same muscle activation, and vice-versa (Bhadra, 2015; Marquez-Chin & Popovic, 2020). This curve defines two key values: the rheobase, which is the minimum current amplitude required to elicit a response with an infinitely long pulse, and the chronaxie, the pulse duration needed to get a response at twice the rheobase current. The chronaxie is characteristically shorter for nerve tissue than for muscle, a vital consideration for targeted EMS (Bhadra, 2015).

For user safety and comfort, the waveform shape is paramount. To prevent the buildup

of residual electrical charge that can cause tissue irritation or damage, the literature strongly recommends the use of biphasic waveforms, which are also considered the most comfortable form of EMS and require less current than monophasic waves (Bowman & Baker, 1985; Diamant & Reilly, 2011; McNeal & Baker, 1988). While symmetrical biphasic pulses are common, balanced asymmetric biphasic pulses are often considered safest for long-term applications, as they ensure a net-zero charge is delivered while allowing precise control over which electrode serves as the primary stimulator (Marquez-Chin & Popovic, 2020). The slope of the waveform also impacts comfort; waveforms with a gentler voltage slope, such as sawtooth waves, can reduce the sensation of pain compared to standard rectangular pulses. However, this comes at a cost, as these gentler waveforms have been shown to produce a lower force output for a given charge, highlighting a direct trade-off between comfort and effectiveness (Ishimaru & Saga, 2023).

In practice, several guidelines help achieve an optimal balance. Proper electrode placement, particularly in proximity to the muscle's motor points (MPs), is essential for maximizing the efficiency of the contraction while minimizing user discomfort (Forrester & Petrofsky, 2004).

The size of the electrodes also involves a key trade-off. While larger electrodes are generally reported to be more comfortable by distributing the current more widely (Alon, 1985; Alon et al., 1994; Patterson & Lockwood, 1991; Verhoeven & van Dijk, 2006), smaller electrodes can offer better selectivity for targeting specific muscles (Kuhn et al., 2010).

A pulse width between 165–300 microseconds has been found to provide a "neutral" sensation, avoiding the uncomfortable tapping or pricking effects associated with lower or higher values (Bowman & Baker, 1985; Gracanin & Trnkoczy, 1975; Knibbe et al., 2018). In conjunction, EMS frequencies in the range of 40–55 Hz are typically used. This range is high enough to produce smooth, fused (tetanic) muscle contractions without a "knocking" sensation, yet not so high as to cause the rapid muscle fatigue associated with higher frequencies (Behringer et al., 2016; Dreibati et al., 2010; Gorgey et al., 2009; Gregory et al., 2007; Knibbe et al., 2018; Peckham & Knutson, 2005). It is also important to note that the relationship between frequency and intensity is not always linear; counterintuitively, lower frequencies (e.g., 10Hz) may require a higher current intensity to achieve the same initial force output as higher frequencies (e.g., 35-50Hz), especially in smaller muscles (Vromans & Faghri, 2017).

2.3.3 Variants and Therapeutic Applications

Beyond its use in haptic feedback, EMS encompasses a wide range of variants with significant therapeutic applications, particularly in rehabilitation and physical therapy. The most prominent of these is Functional Electrical Stimulation (FES), a method that applies EMS to assist or restore a user's voluntary motor functions. FES is used to support a variety of functional movements, including gait for walking (Schauer & Seel, 2018), pedaling for cycling (Mazzoleni et al., 2013), rowing motions (Ye et al., 2021), and hand grasping actions (Freeman et al., 2015). FES systems can be categorized as open-loop, where EMS is manually controlled by a therapist, or closed-loop, which incorporate user bio-signals like electroencephalography (EEG) or EMG to automatically trigger and modulate the EMS (Khan et al., 2023).

A particularly effective closed-loop approach is EMG-triggered FES, where EMS is initiated only after the system detects the user's own voluntary muscle contraction (Bolton et al., 2004; Schauer & Vrontos, 2019; Schauer et al., 2016). This method is considered more effective than passive EMS because it requires active cognitive involvement from the motor cortex. This active participation is crucial for driving neuroplastic changes, a principle derived from Hebb's Law ("cells that fire together wire together"), where coordinating a patient's intent to move with the sensory and motor feedback from the EMS itself promotes functional recovery (Khan et al., 2023; Y. Kim, 2013). The therapeutic benefits are further enhanced when the EMS is synchronized with the performance of specific, functional tasks, a method known as task-oriented EMG-triggered FES (Y. Kim, 2013).

Other specialized techniques target different physiological systems. Tendon Electrical Stimulation (TES), for instance, involves applying current directly to a joint's tendons rather than the muscle belly. This method aims to selectively activate proprioceptive sensory nerves, such as the GTO, to generate a compelling illusion of motion or force with minimal actual muscle contraction (Kajimoto, 2013; Takahashi et al., 2018, 2019). While the force sensation from TES can be ambiguous on its own, its naturalness is significantly enhanced when presented with congruent visual and vibrotactile feedback (Takahashi et al., 2019). For pain management, a well-known variant is Transcutaneous Electrical Nerve Stimulation (TENS), which is characteristically applied at low intensity levels to provide symptomatic relief (Bedwell et al., 2011; Johnson, 2007).

More broadly, EMS serves as an effective therapeutic tool for building and maintaining musculoskeletal health. It is increasingly used to prevent muscle atrophy in immobile patients and can serve as a surrogate for physical activity to reverse the effects of muscle disuse (Magalhães et al., 2019; Nishikawa et al., 2021). For older individuals, combin-

ing EMS with resistance training has been shown to significantly enhance both muscle strength and functional performance (Šarabon et al., 2020). At a fundamental level, EMS can modify the excitability of specific neural pathways, leading to an increase in maximal voluntary force, sometimes even without observable muscle hypertrophy, demonstrating its potent impact on the neuromuscular system (Nishikawa et al., 2021).

2.3.4 Challenges in EMS Delivery

Despite its potential, the practical application of EMS for haptic feedback is complicated by several significant challenges. Historically, the two primary obstacles that have limited the widespread use of surface FES are the difficulty in selectively activating specific muscles and the rapid onset of muscle fatigue compared to physiological activation (Koutsou et al., 2016).

Muscle fatigue is a particularly pressing issue, and its accelerated onset during EMS is a direct consequence of an unnatural, inverted recruitment pattern. Unlike voluntary contractions where smaller, slow-twitch, fatigue-resistant muscle fibers are activated first, EMS preferentially activates larger, fast-twitch, and more easily fatigued fibers (Diamant & Reilly, 2011; Gregory & Bickel, 2005). The response to EMS is not uniform; it's significantly influenced by a muscle's intrinsic characteristics, like its size and fiber composition. While higher pulse frequencies are known to tire muscles more quickly (Behringer et al., 2016), this effect is most pronounced in muscles dominated by fast-twitch (Type II) fibers (Vromans & Faghri, 2018). Complicating matters, while fatigue consistently leads to a decline in force output, the corresponding EMG signal is not a reliable indicator. The EMG signal may increase or decrease during fatigue depending on the muscle's size and fiber composition, making it difficult to monitor fatigue objectively through this channel (Vromans & Faghri, 2017). To mitigate these issues, recent advancements in EMS strategy aim to replace single, wide pulses with a cluster of high-frequency, narrow pulses, using techniques like random amplitude variation to create more asynchronous and natural activation patterns that delay fatigue (Yuan et al., 2025).

The second major challenge is the poor muscle selectivity of surface EMS, which makes it difficult to precisely target and activate only the desired muscles (Gregory & Bickel, 2005). To address this, multi-pad electrode arrays have been developed to allow for better spatial and temporal control of the electric field, thereby improving muscle selectivity. These arrays also enable asynchronous EMS patterns across different muscle regions, which can further help manage fatigue (Koutsou et al., 2016).

Finally, several perceptual and practical issues must be considered. The force gener-

ated by EMS can be perceptually overestimated; one study found that an EMS-induced force was perceived as subjectively twice as strong as an equivalent physical force, likely due to the simultaneous stimulation of both efferent motor and afferent sensory pathways (Ishimaru & Saga, 2023). User discomfort can also be a limiting factor, though it can be managed by using specific waveforms, such as asymmetric biphasic pulses, which are designed to minimize the activation of pain-conducting nerve fibers (Yuan et al., 2025). Lastly, the inherent variability of skin impedance—which changes with moisture and electrode contact—poses a significant challenge to delivering consistent sensations and underscores the need for adaptive, closed-loop systems that can adjust to these changes in real-time (Yang et al., 2025).

2.3.5 Wearable and Prototyping Advances

Prototyping novel applications with EMS has historically been a significant challenge, requiring researchers to possess deep, interdisciplinary expertise in custom hardware design, software development, and the physiological nuances of electrode placement and user calibration (Pfeiffer et al., 2016). To address this, the creation of wearable haptic experiences has been made more accessible through the development of open-source prototyping toolkits. These toolkits lower the barrier to entry for HCI research by abstracting away hardware complexity, often by repurposing commercial TENS/EMS devices as reliable signal generators controlled via a simple wireless module (Pfeiffer et al., 2016).

Recent trends in the field of electrical haptics are moving decisively towards flexible and wearable devices designed for everyday use. However, current research remains heavily concentrated on the hands and forearms. The development of comprehensive, full-body haptic systems needed to create truly deep and immersive experiences remains a largely underexplored frontier (Vrontos et al., 2024; Yang et al., 2025).

Perhaps the most significant limitation of current electrotactile and EMS-based haptic research is its reliance on open-loop systems that use predefined, “one-size-fits-all” parameters. A critical and widely acknowledged future direction is the development of adaptive, closed-loop algorithms. Such systems would leverage artificial intelligence and real-time physiological data to enable truly personalized and automated haptic feedback, tailoring the experience to the individual user’s body and perceptual thresholds (Vrontos et al., 2024; Yang et al., 2025).

2.4 Human Factors in Haptic Perception

The degree to which a user feels present and engaged in a virtual environment is not solely a function of technological fidelity. It is also deeply influenced by a range of human-centric factors that mediate the experience. These contributing factors can be grouped into four major categories: Control Factors, which relate to the immediacy and intuitiveness of user input; Sensory Factors, concerning the richness and modality of the feedback provided; Distraction Factors, such as awareness of the interface itself; and Realism Factors, which govern the consistency of the virtual experience with real-world physics and expectations (Witmer & Singer, 1998). This section explores these elements, with a focus on the ergonomic and physiological variables that shape haptic perception.

2.4.1 Ergonomic and Task-Related Factors

Haptic perception is a fundamentally active process, distinguished by a tight sensorimotor loop that inseparably integrates intentional action with sensory feedback (Biswas & Visell, 2021). This inseparability is so profound that even a familiar motor task like grasping a pen becomes extremely difficult if the skin is anesthetized, highlighting how action and sensation are deeply integrated. This creates a unique bidirectional information channel, where the user's actions generate the very sensory feedback they perceive, allowing them to simultaneously act upon and understand the virtual environment (Kaber & Zhang, 2011). The nature of the user's goal further shapes this interaction; haptic tasks can be broadly categorized as either motor control tasks, where the primary goal is to manipulate objects, or perception tasks, where the goal is to recognize an object's properties (Kaber & Zhang, 2011).

Several specific ergonomic factors critically influence the effectiveness of this sensorimotor loop. The temporal relationship between sensory modalities is paramount. A desynchronization, or time lag, of as little as 150 ms between visual and haptic feedback can significantly degrade motor task performance, as it breaks the user's intuitive sense of cause and effect (Salvendy, 2012). In some cases, ergonomic factors can be deliberately manipulated to create illusory sensations. For example, altering the control-display (C/D) ratio in pseudo-haptics intentionally creates a sensorimotor conflict between what the user sees and what their proprioceptive system feels. This mismatch can generate a compelling illusion of weight or resistance that systematically influences a user's physiological lifting patterns (Moosavi et al., 2024).

Crucially, the user's static posture also fundamentally alters the haptic output. Research by Leedham and Dowling (1995) demonstrates that while EMS produces a con-

stant level of myoelectric activation across different joint angles, the resulting physical torque varies significantly due to changes in the muscle's moment arm and force-length relationship. This is confirmed specifically for the triceps—the primary target for antagonist weight simulation—by Memberg et al. (2003), who found that stimulated extension moments were significantly weaker at 30° of flexion compared to the peak torque generated at 90°. Consequently, a constant EMS pulse generates inconsistent force sensations depending on the limb's position, necessitating posture-dependent scaling to maintain haptic consistency. Conversely, the influence of dynamic task factors appears less critical for certain biomechanical relationships. X. Wang et al. (2017) developed a biomechanical model linking upper-arm muscular strain to joint torque and found that, unlike the significant effects of elbow angle, the angular velocity of the movement (tested between $60°/s$ and $120°/s$) had no statistically significant impact on the torque generation ratio. This implies that while haptic systems must rigorously compensate for static ergonomic factors (force-length relationship), the force-velocity relationship may be sufficiently stable to be treated as a constant in simplified biomechanical models.

However, the haptic system can also be surprisingly robust. The addition of a gross motor task, such as walking on a treadmill, has been shown to have no significant impact on the ability to discriminate handheld weights, suggesting the perceptual system is adept at filtering out the sensory "noise" from a secondary motor task to focus on the primary haptic goal (Chen et al., 2021). Conversely, other factors can disrupt the experience. High cognitive load required to interpret ambiguous or complex multisensory cues can draw the user's attention away from the task and onto the interface itself. Furthermore, factors like a heightened susceptibility to cybersickness, particularly in older adults, can lead to disorientation and a reduced sense of presence, posing a significant challenge for inclusive haptic design (Schaumburg et al., 2025).

2.4.2 Physiological and Individual Variability

Engineering high-fidelity haptic feedback is a daunting challenge, as any technology must contend with the human body's extraordinary sensory and mechanical capabilities. The skin is not merely a passive surface but a complex, active medium capable of discriminating features on the nanometer scale (Biswas & Visell, 2021). Furthermore, perception is not a direct readout of sensory information; even the haptic perception of complex shapes is biased towards representations of simple "primitives", suggesting the brain actively simplifies incoming data to fit pre-existing models (Ehrich et al., 2008).

Beyond these universal complexities, significant inter-subject variability introduces another layer of challenge. This variability is multifaceted, stemming from both physio-

logical and perceptual differences between individuals. On a physiological level, factors such as age-related declines in proprioceptive acuity, slower sensorimotor processing (Schaumburg et al., 2025), and anthropometric characteristics like Body Mass Index (BMI) or muscle mass directly influence the physical medium through which feedback is delivered. This is particularly critical for EMS, where these factors can alter skin impedance and current diffusion. For instance, while biological sex is often cited as a variable, Seno et al. (2019) demonstrated that sex differences in electrical sensitivity—specifically the lower current perception thresholds observed in females—are mediated by body composition: when adjusted for body fat and water percentage, these sex differences disappear. Contrary to the assumption that fat purely insulates, it forces electrical current to flow preferentially through the dermis and epidermis, thereby exciting cutaneous nerve fibers more easily in individuals with higher subcutaneous fat (Seno et al., 2019). de Jesus Guirro et al. (2015) further demonstrated that even when BMI is within normal standards, age acts as an independent factor that significantly elevates these thresholds at higher frequencies.

Crucially, individuals also exhibit wide-ranging perceptual differences, which are evident in their unique STs, MTs, and PTs. This sensitivity profile is often non-linear; Maffiuletti et al. (2008) found that while women required significantly less current to reach sensory (-43%) and supramotor (-17%) thresholds, there was no significant difference between sexes in the current required to trigger the initial motor response. de Jesus Guirro et al. (2015) corroborated this dissociation, finding that STs were significantly lower in women than in men across age groups, while no definitive pattern emerged for MTs based on sex. However, at this MT, women reported significantly higher pain scores (+112%), indicating a distinct dissociation between muscle activation and comfort (Maffiuletti et al., 2008). This discrepancy reveals that simple demographic-based adjustments are insufficient, necessitating individual calibration to balance effective actuation with user comfort.

Distinct from these electrical sensitivities, natural haptic force control shows a different pattern. Brown et al. (2010) observed that while men were significantly steadier than women during isometric contractions, this difference was primarily predicted by absolute strength; when controlling for maximal voluntary contraction (MVC), the difference in steadiness became non-significant ($p = 0.69$). This suggests that for motor stability, physical strength is a determining factor (Brown et al., 2010). However, this relationship does not transfer to sensory perception. Niespodziński et al. (2018) found that while long-term physical training significantly enhances proprioceptive acuity—with gymnasts demonstrating superior Force Sense and Joint Position Sense—this improvement is not a function of raw power. Critically, they established no significant correlation between

maximal muscle strength and proprioceptive errors. This implies that, while strength aids motor stability, haptic sensitivity is a refined, trainable neural skill that does not automatically scale with physical capacity.

This high degree of individual difference in perception is not confined to physiological tasks or EMS; it is also fundamentally shaped by the user's cognitive state. Zhou et al. (2007) introduced the "Spare Cognitive Capacity" theory to haptic interactions, demonstrating that the utility of haptic feedback is heavily dependent on user expertise. They found that while experienced users utilized haptic cues to maintain accuracy under high cognitive load, novices—whose mental resources were fully consumed by the motor task—failed to benefit from the feedback and, in some cases, even found it distracting. Research into other haptic methods, such as modulating a controller's trigger resistance to simulate weight, reveals similarly large perceptual differences; some participants readily form the intended association, while others may not consciously notice the feedback at all (Stellmacher et al., 2022).

Collectively, this high degree of variability is the primary reason why a "one-size-fits-all" approach to haptic design is fundamentally flawed. It underscores the necessity for adaptive, personalized systems that can be calibrated to an individual's unique physiological and perceptual profile, a central theme that motivates the empirical work of this thesis.

2.4.3 Multisensory, Material, and Visual Influences

Haptic perception rarely occurs in isolation and is strongly influenced by information from other senses, particularly vision. A critical factor in these multimodal environments is sensory dominance, where the brain weights inputs differently depending on the context. In many cases, vision dominates haptics; for example, a strong visual stimulus can overshadow subtle haptic cues (Stellmacher et al., 2022), and vision is often the dominant sense in the perception of properties like stiffness (Salvendy, 2012). This dominance extends beyond material properties to the perception of shape. Hettiarachchi and Wigdor (2016) demonstrated that the "visual dominance" of the sensorimotor system allows for the opportunistic use of everyday physical objects as haptic proxies in AR. By dynamically rescaling virtual objects to visually align with the salient geometric primitives of a physical prop, their system effectively leveraged visual cues to mask the geometric mismatches between the real and virtual objects.

Perhaps the most famous demonstration of this visual influence is the SWI, a robust phenomenon where a larger object is consistently perceived as being lighter than a smaller object of the exact same mass (Jones, 1986). The predominant explanation

for this illusion is the "prediction mismatch" theory. This theory posits that the visual system's perception of the larger size creates a strong expectation that the object will be heavier, causing the brain to prepare an oversized motor command to lift it. When the object is lifted far more easily than anticipated, the brain resolves this sensory conflict by generating the illusion of unexpected lightness (Jones, 1986; van Polanen & Davare, 2019). An alternative theory suggests the illusion may arise from a more fundamental sensory interaction where the haptic system inherently combines an object's mass and volume, consistent with the idea that perceived weight is a function of rotational inertia (Valdez & Amazeen, 2008). The SWI is so powerful that it can be replicated in VR using purely visual stimuli, even without any conflicting haptic feedback. This contrasts with other visual weight illusions (e.g., based on material), which tend to be inverted in VR when haptics are absent, suggesting the SWI operates via a unique perceptual mechanism (Maehigashi et al., 2021).

However, in other contexts, haptics can be the dominant sense. In tasks requiring precise spatial targeting, C.-G. Lee et al. (2015) found that users prioritized haptic feedback over visual cues when determining if they had reached a target wall, despite the presence of spatial discrepancies. Crucially, this haptic dominance was not static but increased significantly as the stiffness of the virtual object increased, suggesting that the brain dynamically re-weights sensory signals in favor of the most mechanically reliable source. This principle of tactile dominance is also clearly demonstrated in the Material-Weight Illusion (MWI), where tactile cues—such as the perceived density of a material—exert a significantly stronger influence on perceived heaviness than visual appearance alone. In cases of direct conflict, such as an object that looks like styrofoam but feels like metal, the tactile information can effectively override the visual input to dictate weight expectations (Naylor et al., 2022).

This process of sensory arbitration is not limited to cross-modal conflicts; it also manifests as an internal competition within the haptic channel. Li and Seifi (2025) identified a "mutual masking" effect when combining vibration and EMS, where the brain's internal negotiation for neural resources results in a bidirectional trade-off: while high-amplitude vibration can dominate and suppress the cutaneous discomfort of EMS, the EMS reciprocally masks the user's sensitivity to vibration, significantly increasing the Just Noticeable Difference (JND) for frequency discrimination. Collectively, these phenomena highlight that haptic perception is the result of a continuous, dynamic weighting of competing sensory signals.

Finally, the visual representation of the user's own body within the virtual environment can profoundly impact their subjective experience. While the choice of a virtual hand model—from an abstract sphere to a realistic hand—may not affect objective task

performance, more realistic, human-like representations consistently provide a better user experience. They lead to a significantly stronger sense of body ownership, connection, and enjoyment, highlighting that visual form is a key factor in shaping the user's subjective feelings of presence and immersion (Balcomb et al., 2023).

2.4.4 EMS Strategies for Realism

Early strategies for rendering weight with EMS focused on simplified, single-muscle approaches. Foundational work by researchers like Faltaous et al. (2022) demonstrated the feasibility of stimulating a single antagonist muscle, the triceps brachii, to convincingly increase a virtual object's perceived heaviness. Similarly, Galofaro et al. (2022) attempted a user-specific calibration model; however, their approach remained fundamentally laboratory-bound. To map EMS intensity to perceived force, their calibration necessitated a rigid, single-degree-of-freedom platform equipped with an external load cell, restricting the user to a static 45-degree posture. Furthermore, the system stimulated only one muscle at a time and relied on manual anthropometric measurements to calculate torque. This cumbersome physical setup not only severely compromises the system's mobility and ease of use, but also fails to capture the multi-muscle coordination required for a truly realistic, unconstrained haptic experience.

Despite these promising early findings, a notable limitation of single-muscle EMS is its reduced perceived realism, a problem that becomes particularly evident during active tasks where a user's own movements can interfere with the feedback (Y. Kim et al., 2024). To create a more natural sensation, subsequent research showed that stimulating multiple muscles is a more effective strategy for emulating the body's complex biomechanical response to holding an object (Cheng et al., 2024; Lopes et al., 2018). However, even this pioneering multi-muscle work often lacked a quantitative relationship between the EMS and the perceived sensation, with the feedback being primarily binary—distinguishing only between "force present" and "no force" (Lopes et al., 2017).

The evidence presented in this thesis confirms that a dual-muscle EMS strategy is superior to single-muscle approaches for both perceived effectiveness and realism (Vrontos, Zolnouri, Mertens, et al., 2025). This aligns with findings from human perception studies which show that factors beyond a single muscle group, such as wrist inertia, are crucial for the sensation of heaviness (Waddell & Amazeen, 2017). Indeed, while the foundational work of Galofaro et al. (2022) focused on a single-muscle approach, it was participant feedback within that very study that first suggested multi-muscle EMS would feel more realistic. This observation, combined with the previously mentioned limitations, highlighted a clear gap in the literature: the need for a more flexible, multi-

muscle, and sensor-free approach that can create a precise, quantitative link between EMS parameters and a user's subjective perception. The scientific work reported in this thesis aimed at addressing this specific gap.

2.5 Personalization in HCI and Haptics

2.5.1 The Rationale and Frameworks for Personalization

Widespread adoption of haptic technology is unlikely without systems that can adapt to the individual, as a "one-size-fits-all" approach fails to account for the significant differences in how users perceive, prefer, and cognitively interpret haptic sensations (Seifi, 2019). This need for personalization is a core tenet of User-Centered Design (UCD), which prioritizes the user's needs, goals, and preferences throughout the design process to create more intuitive and effective experiences (Kotian & Nandipi, 2024). Instead of a technology-centered approach that focuses purely on engineering capabilities, UCD prioritizes a deep understanding of user needs and limitations from the outset. This principle is especially critical for haptic systems, where the experience is profoundly subjective. For the EMS-based haptics central to this thesis, a UCD approach means moving beyond universal parameters and instead designing systems that can account for significant inter-subject variability. The significant inter-individual variability in physiological and cognitive capabilities, particularly in diverse populations such as older adults, further necessitates the design of adaptive interfaces that can be calibrated to a user's specific EMS thresholds and motor abilities (Schaumburg et al., 2025).

Broadly, personalization can be divided into two categories: customization, where the user explicitly adjusts settings, and adaptation, where the system automatically adjusts itself based on an underlying user model (Neumayr & Augstein, 2020). Because manipulating low-level engineering parameters is often beyond the capacity of end-users, effective personalization tools must operate within the user's own cognitive and linguistic domain (Seifi & MacLean, 2017). To address this, frameworks have been proposed that use intuitive mechanisms like choosing, tuning, and chaining to allow users to personalize their experience in a more accessible way (Seifi, 2019). To bridge the gap between engineering parameters and user perception, the theoretical model of 'haptic facets' has been introduced. This model encapsulates the various cognitive schemas—such as sensory, emotional, or metaphoric—that people use to describe touch, thereby creating a structured perceptual space for both design and personalization (Seifi, 2019; Seifi & MacLean, 2017).

Effective personalization, particularly automated adaptation, relies on a robust user model. Such models must go beyond traditional demographic data to capture a wide range of individual characteristics, including a user's goals, interests, interaction history, and intrinsic human factors like their unique cognitive, visual, and emotional processing characteristics (Germanakos & Belk, 2016; Neumayr & Augstein, 2020). Ultimately, user preferences are highly context-dependent, with factors like cognitive styles, emotional states, and the specific task at hand all influencing performance and satisfaction (Germanakos & Belk, 2016; Roy et al., 2024). This dynamic interplay underscores the need for adaptive systems that can account for the variability of both the user's internal state and the external environment (Rokhmanova, 2023).

2.5.2 Methods for Personalizing Haptic Feedback

Methods for personalizing haptic feedback range from direct user manipulation to sophisticated, automated adaptation driven by ML. When given direct control, users express a lower preference for simply 'choosing' from a predefined list of effects, instead favoring a 'tuning' approach that offers a balance between design control and convenience (Seifi, 2019). For such end-user customization to be effective, it should be limited to parameters that are intuitive and do not corrupt the core artistic intent of the haptic designer. Research has identified intensity and spatial density as suitable for this purpose, as users treat them as independent and meaningful dimensions of a haptic experience, whereas parameters like timeliness are too fundamental to the core design (Roy et al., 2024).

A data-driven approach is therefore necessary to move beyond static, "one-size-fits-all" parameters. ML has emerged as a fundamental technology for this purpose, demonstrating in related biomedical fields its ability to process vast datasets and deliver personalized insights that can augment clinical decisions (Rajkomar et al., 2019). The primary strength of ML lies in its focus on accurate prediction; it excels at making reliable classifications from complex, high-dimensional inputs, such as correctly identifying malignant tumors with a high degree of sensitivity and specificity (Sidey-Gibbons & Sidey-Gibbons, 2019). The integration of ML into HCI is pivotal for moving beyond static interfaces toward dynamic systems that can learn from and adapt to user behavior (Gupta et al., 2024). ML enables a more implicit form of personalization, overcoming the challenge of users being unwilling to explicitly provide personal data by inferring their characteristics and preferences directly from their interaction behaviors (Germanakos & Belk, 2016). A key goal is to map high-level, user-centric schemas to the underlying engineering parameters. For example, ML can be used to power a perceptual 'slider' for an attribute like 'liveliness' by learning the complex combination of low-level parameters that produces

this subjective feeling for an individual (Seifi & MacLean, 2017). This allows artificial intelligence to analyze a user's interaction patterns in real-time and dynamically adjust haptic feedback (Emami et al., 2024).

In the context of EMS, ML is used to create more personalized experiences and optimize muscle activation (Ghosn, 2023). Automatic calibration systems are critical for personalization, with some approaches using real-time optical sensing to monitor muscle contractions and create dynamic models of an individual's unique responses (Gange & Knibbe, 2021; Hosono et al., 2022). These data-driven models align with other personalization techniques, such as using ML to automatically tailor EMS amplitudes (Vrontos, Zolnouri, Nitsch, et al., 2025). Ultimately, personalization can be framed as an information-theoretic problem, where the goal is to identify the optimal configuration of hardware and software signals to maximize the information transfer for a specific user (Valdivia et al., 2026). Emerging trends like affective computing, which focuses on creating intelligent systems that can recognize, interpret, and respond to human emotions and intentions, aim to push this further by enabling more deeply personalized and empathic interactions (Kotian & Nandipi, 2024).

2.5.3 Benefits and Challenges of Personalized Systems

Personalizing haptic feedback offers significant benefits for motor learning, user experience, and the long-term adoption of assistive technologies. Studies have shown that allowing users to customize haptic feedback during a motor learning task can significantly improve objective performance and enhance the subjective sense of agency (K. Lee et al., 2025). Users demonstrate clear learning strategies when given this control, preferring stronger, more assistive feedback in the early stages and transitioning to milder feedback as their skills improve (K. Lee et al., 2025). Beyond performance, personalizing haptic feedback has been shown to reduce the cognitive load of interacting with a system, leading to a measurable decrease in perceived mental demand and effort (Hazra & Shiakolas, 2024). This reduction in training time and cognitive overload is critical for improving user acceptance and preventing device abandonment, particularly in assistive systems (Hazra & Shiakolas, 2024).

The importance of this feedback is rooted in the fundamental integration of somatosensory feedback with motor control. This kinesthetic awareness, which as previously detailed is derived from a variety of mechanoreceptors including muscle spindles, GTOs, and joint receptors, provides the crucial signals that inform the body of its state (Demain et al., 2013). The complex skill of identifying an object by touch alone (stereognosis) is an active process requiring the tight integration of motor exploration and sensory feed-

back. Consequently, clinical evidence shows that somatosensory loss is directly linked to impaired regulation of grip forces, uncoordinated movement, and reduced functional recovery, highlighting the critical role of haptics in rehabilitation (Demain et al., 2013).

However, the implementation of personalized systems introduces a unique set of challenges that must be addressed for responsible and effective deployment. While powerful, the use of ML raises significant ethical considerations (Gupta et al., 2024):

- Data Privacy: Personalized models require sensitive physiological and biometric data. The collection, storage, and use of this data demand robust privacy protocols to protect user information.

- Algorithmic Bias: If the training data is not sufficiently diverse—a known issue in the field, as highlighted in the systematic literature review (Chapter 3)—the resulting models may perform well for some demographic groups but poorly for others, potentially leading to inequitable or ineffective experiences.

- Transparency: Many advanced ML models operate as "black boxes", making it difficult to understand the reasoning behind a specific decision (e.g., why a certain EMS level was chosen). This lack of transparency can be a barrier to trust and safety, particularly in therapeutic contexts.

Beyond the ethics of ML, the evaluation of haptic systems is itself a major challenge. Because the perception of feedback is highly subjective and varies greatly between individuals, it is difficult to make objective, "apples-to-apples" comparisons between different technologies or studies, necessitating robust and well-designed user research (Emami et al., 2024). This directly impacts real-world adoption; a key obstacle preventing the widespread clinical use of promising haptic therapies is the lack of predictive models that can forecast outcomes. A therapist needs to know if a technology is likely to be effective for a specific patient before investing significant time and resources in treatment (Rokhmanova, 2023). Finally, while most personalization focuses on the individual, a significant conceptual challenge remains for collaborative environments: how to develop group models that can effectively aggregate the diverse, and potentially conflicting, needs of multiple users into a coherent shared experience (Neumayr & Augstein, 2020).

2.6 Summary and Implications for Research Objectives

This chapter reviewed the theoretical foundations of haptic feedback, establishing that the simulation of weight in virtual environments involves a complex interaction of biomechanical, physiological, and perceptual factors. The literature indicates that weight perception is not a unitary sensation but a multimodal construct derived from the sense of effort, proprioceptive afference, and visual expectations.

The theoretical constraints and physiological mechanisms identified in this chapter highlight specific challenges that directly inform the empirical investigations of this thesis:

- **Muscle Recruitment Strategies:** Natural object manipulation relies on the coordinated activation of agonist and antagonist muscles. In contrast, existing EMS applications often utilize simplified single-muscle EMS. This discrepancy suggests a need to systematically compare the perceptual realism of single- versus dual-muscle EMS strategies to determine if multi-channel EMS provides a more accurate approximation of physical weight.
- **Physiological Variability and Calibration:** The review of physiological factors—including body composition, skin impedance, and sensorimotor processing—demonstrates that sensitivity to EMS varies significantly and non-linearly between individuals. The observed dissociation between PT and MT indicates that fixed-parameter systems are insufficient. Consequently, the development of data-driven models capable of personalizing feedback to an individual's specific physiological profile is a critical requirement for effective haptic rendering.
- **Psychophysical Context:** Proprioceptive acuity is context-dependent, influenced by variables such as joint angles and stimulus magnitude. To transition EMS from a feasibility concept to a robust interface, it is necessary to characterize how ergonomic factors, specifically user posture and weight magnitude, modulate the required EMS intensity and subjective realism.
- **Multisensory Integration:** The brain integrates conflicting sensory inputs by weighting them based on reliability, often resulting in visual dominance. Understanding the interaction between EMS-induced proprioception and dominant visual cues in VR is essential for managing sensory conflicts and maintaining user immersion.

Having established the theoretical basis for these factors, the following chapter presents a systematic literature review of the state-of-the-art in EMS-based haptics, identifying the specific methodological gaps that the empirical work of this thesis aims to address.

3 State of the Art: A Systematic Literature Review[1]

This chapter establishes the state of the art in using EMS for kinesthetic feedback, providing the theoretical foundation for the empirical studies that follow.

3.1 Aims and Research Questions of the Review

This systematic literature review comprehensively investigates the current state of the art in utilizing EMS for kinesthetic feedback. This review not only synthesizes existing knowledge but also identifies gaps that motivate the empirical investigations in this thesis. The review is structured around several primary research questions designed to elucidate the role, potential, and prevailing methodologies of EMS within this domain.

First, the review surveys the landscape of applications where EMS has been employed for kinesthetic feedback. This involves cataloging the specific use cases reported in the literature to map the breadth of its application and identify the anatomical areas targeted for EMS.

Subsequently, a detailed examination of the EMS parameters and settings reported in these studies is undertaken. By analyzing the specific electrical characteristics (e.g., frequency, pulse width, amplitude), this section aims to understand how these parameters

[1]This chapter is based on the author's previously published, peer-reviewed article: Vrontos, A., Nitsch, V., & Brandl, C. (2024). Electrical Muscle Stimulation for Kinesthetic Feedback in AR/VR: A Systematic Literature Review. *Multimodal Technologies and Interaction, 8*(2), 7. For this publication, the author of this thesis led the conceptualization, developed the systematic review methodology, conducted the investigation and data curation, and wrote the original manuscript draft. Prof. Dr.-Ing. Verena Nitsch and Dr.-Ing. Christopher Brandl contributed through supervision, funding acquisition, and the review and editing of the final manuscript. Specifically, Sections 3.1, 3.2, and 3.4 have been adapted and paraphrased for the context of this thesis, while Section 3.3 is reprinted verbatim. The original work is licensed under a Creative Commons Attribution 4.0 International License.

influence the quality of the rendered kinesthetic sensations. This analysis is critical for establishing a baseline of effective EMS protocols.

Finally, a critical analysis of the research methodologies employed in the selected literature is conducted. This includes an assessment of participant demographics, sample sizes, and the nature of the outcome measures used—both subjective and objective. The purpose of this methodological critique is to identify common practices, highlight potential gaps, and inform the experimental design of the studies presented in the subsequent chapters of this thesis.

3.2 Review Methodology

The methodology for this systematic review was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework.

To ensure a thorough and systematic exploration of the literature, search terms were carefully selected to encompass the key aspects of EMS for kinesthetic feedback. The search strategy was organized around three conceptual pillars:

- Electrical Stimulation (I): Terms such as "electromyostimulat*", "electrostimulat*", "muscle* NEAR/2 stimul*", "electric* NEAR/2 stimul*", and "fiber* NEAR/2 stimul*" were used to capture studies focused on the application of electrical impulses for muscle activation.
- AR and VR (II): Terms including "virtual reality", "augmented reality", and "mixed reality" were incorporated to identify environments where EMS enhances kinesthetic experiences.
- Kinesthetic Feedback and Learning (III): Terms like "motor NEAR/2 learn*", "motor NEAR/2 train*", "move*", "motion", "pose*", "posture*", "kinematic*", "kinetic*", "kinaesthetic*", "tactil*", "force*", and "kinesth*" were selected to include research on movement, posture, and physical feedback.

The complete search query executed in the Web of Science database is as follows:

```
TI=(electromyostimulat* OR electrostimulat* OR muscle* NEAR/2 stimul*
OR electric* NEAR/2 stimul* OR fiber* NEAR/2 stimul*) (I)
AND
TS=(motor NEAR/2 learn* OR motor NEAR/2 train* OR move* OR motion
OR pose* OR posture* OR kinematic* OR kinetic* OR kinaesthetic* OR tactil*
```

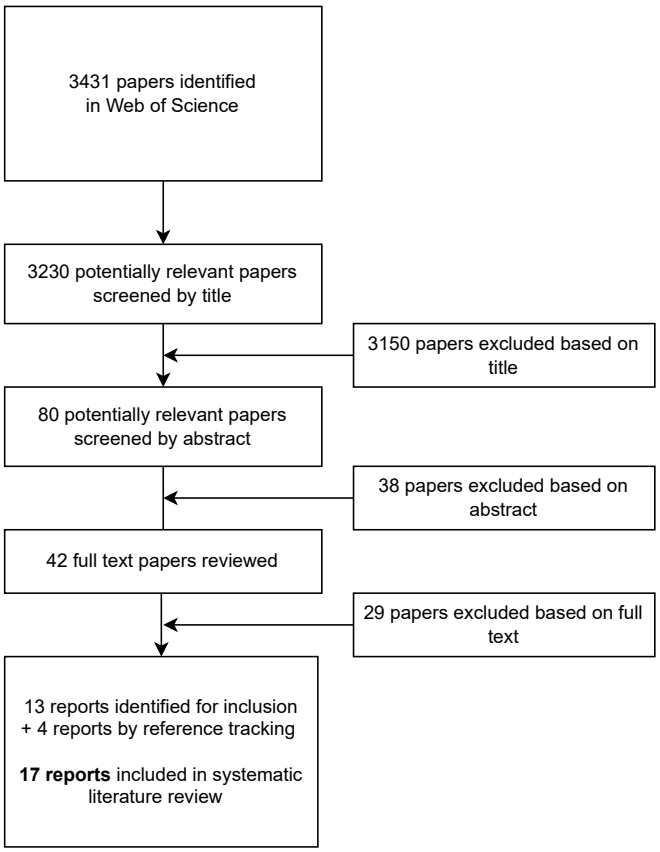


Figure 3.1: PRISMA flowchart illustrating the literature selection process. Reprinted from Vrontos et al. (2024), licensed under CC BY 4.0.

`OR force* OR virtual reality OR augmented reality OR mixed reality OR hapt* Or kinesth*). (II, III)`

Inclusion criteria were defined as:

- Studies exclusively utilizing non-invasive EMS to isolate its effects, excluding invasive methods due to differing risks.
- Exclusion of research combining EMS with other modalities (e.g., mechanical or vibrotactile) to focus solely on EMS-specific impacts.
- Limitation to English-language publications for consistency and feasibility.

The selection process followed PRISMA protocols: initial title screening, abstract review, and full-text evaluation, as depicted in Figure 3.1. For ambiguous cases, full texts were examined. References from selected papers were also reviewed to identify additional relevant studies.

3.3 Synthesis of Findings: Applications, Parameters, and Measures[2]

This section presents the review findings in terms of applications of EMS in kinesthetic feedback, EMS parameters that were used across the identified literature, and the sample demographics and measures that were used in the studies of the identified literature. Additionally, details such as the specific body parts where EMS was applied, the experimental setups, and the study outcomes can be found in Table A.1 in Appendix A.

3.3.1 Kinesthetic Feedback Applications

The use of EMS for kinesthetic feedback has been explored in various applications, demonstrating its potential to enhance user experiences and interactions. This section presents a compilation of the applications identified in the literature.

Force Feedback: One important application of EMS is for producing force feedback. Lopes et al. (2018) used EMS to simulate frictional forces, using counterforces on the user's forearm during virtual interactions. This approach enabled users to feel resistance akin to pushing a physical object. Pfeiffer et al. (2019) explored the potential of EMS-based feedback in virtual training environments. They employed EMS to simulate kinesthetic feedback, such as the sensation of a hand being pushed towards or pulled away from a button, thus aiding trainees in memorizing workflows more efficiently. Similarly, Lopes and Baudisch (2013) utilized EMS to create counterforces on the forearm during mobile gaming. By generating force feedback with

[2]This section is reprinted verbatim from: Vrontos, A., Nitsch, V., & Brandl, C. (2024). Electrical Muscle Stimulation for Kinesthetic Feedback in AR/VR: A Systematic Literature Review. *Multimodal Technologies and Interaction, 8*(2), 7. Open Access. This article is licensed under a Creative Commons Attribution 4.0 International License.

forces up to 18.7 N, they simulated the haptic sensation of interacting with objects within the game. Khamis et al. (2019) also employed EMS to create an immersive force-feedback experience during VR game cut-scenes, heightening the sense of user involvement. In a further advancement, J. Lee et al. (2020) developed a force response model specifically for activating forearm extensor muscles via EMS. This model, using pulse parameters as input, accurately forecasts the elicited force response, contributing significantly to the refinement of EMS-based force-feedback rendering.

Virtual Wall Interactions Creating the perception of touching a virtual wall is a challenging task in VR environments. Researchers have explored different approaches using EMS to enhance the haptic feedback during virtual wall interactions. Lopes et al. (2017) developed a wearable system that utilizes EMS to prevent the user's arm from passing through a virtual wall. By applying short-duration stimuli, they create a repulsion effect that gives the user the sensation of touching the wall. Another approach proposed by Harris et al. (2016) involves stimulating the biceps brachii muscle to create a damping behavior for the elbow joint angle, improving the haptic sensation during virtual wall interactions.

Stiffness Perception EMS has also been investigated to simulate the perception of stiffness in virtual objects. Kurita et al. (2016) conducted experiments to produce different levels of stiffness using EMS. Although they observed a statistically significant correlation between target stiffness and perceived stiffness, they noted the importance of stimulating multiple muscles simultaneously to achieve a more realistic sensation. Furthermore, the same approaches proposed by Harris et al. (2016) and Lopes et al. (2017) for simulating virtual wall interactions can be used to convey the stiffness of virtual objects.

Assigning Weight to Virtual Objects Several research initiatives have employed EMS to convey a sensation of "virtual weight" when users handle virtual objects. Lopes et al. (2017) applied EMS to stimulate the triceps muscle of users. This stimulation creates a scenario where the users need to actively use their biceps muscle to counterbalance the effect. The interaction between the stimulated triceps and the actively engaged biceps helps in creating a sensation of holding an object with weight in a virtual environment. Meanwhile, in a study conducted by Faltaous et al. (2022), participants performed dumbbell biceps curls as EMS was applied to four distinct muscles

implicated in the arm movements. Their findings indicated that the biceps brachii and triceps brachii's actuation had the most significant impact on weight perception. Lastly, Galofaro et al. (2022) developed an experimental setup to enhance user interactions with VR objects. Specifically, their focus was on users holding and lifting a virtual cube, with the key aspect being the ability to perceive the cube's weight as if it were a real object. In a virtual environment, when a user 'lifts' the virtual cube, the stimulation of the triceps creates a physical sensation that mimics the effort required to lift a real object. This muscle contraction, and the resulting extension force at the elbow, effectively simulates the torque or rotational force one would experience while actually lifting an object.

Perceiving Impact with Virtual Objects The use of EMS to create the sensation of having an impact with virtual objects has been a subject of exploration in recent studies. Kruijff et al. (2006) pioneered the exploration of EMS for kinesthetic feedback, termed 'pseudo-haptic' feedback in their research, by replicating the sensations of bullet impacts or explosions in gaming scenarios. Their research covered various aspects such as the perception of pain, reaction loss, feedback quality, excitement, and the likelihood of continued use. In Lopes et al. (2018) the user pushed a virtual object and when the object "hit" a wall in the physical environment, the user felt a bumping sensation on their shoulders and wrists. Additionally, Ishimaru and Saga (2020) focused on creating the sensation of bumps during virtual interactions. They demonstrated that electrical stimulation is superior to mechanical vibration for simulating large bumps and uneven surfaces, providing a more realistic haptic experience.

Interacting and Handling Objects In their innovative study, Lopes, Ion, et al. (2015) introduced the concept of proprioceptive interaction, exemplified through a wearable prototype that leverages the user's proprioceptive sense for both input and output. This means using body pose as a bidirectional communication channel between the human and the computer. The study demonstrated two forms of interaction: symmetric, where input and output occur in the same limb, and asymmetric, involving different limbs for input and output. For instance, users manipulated a video-scrubbing tool through wrist flexion, with EMS stimulating their wrist muscles for improved control in a symmetric interaction. In contrast, an asymmetric interaction was showcased where users played a solitaire game and a modified version

of 'Pong', with one hand controlled by the EMS device and the other by the user. Lopes, Jonell, and Baudisch (2015) delves into various applications of EMS in guiding hand movements for operating objects, assisting with the use of multifunctional tools, and facilitating interactions with objects that change dynamically. This includes using EMS for preemptive guidance during diverse interactions with objects, offering a more intuitive and responsive experience.

Other applications EMS has also been utilized to facilitate correct movements for learning to play musical instruments (Ebisu et al., 2017) and enhance the haptic feedback in a Mixed-Reality (MR) tennis game (Farbiz et al., 2007). Furthermore, Pfeiffer et al. (2013) demonstrates the use of EMS as a haptic feedback method in interactive public display environments, highlighting its potential as a subtle and privacy-preserving alternative to visual and acoustic feedback. The authors envision the integration of EMS technology into smart clothing or wearable devices to enhance interaction in public spaces.

3.3.2 EMS Parameters

The utilized pulse form was mentioned in 6 out of the 17 reports. Notably, among those 6, biphasic pulses were the predominant type used, as cited in the references Harris et al. (2016), Kruijff et al. (2006), J. Lee et al. (2020), Lopes, Ion, et al. (2015), and Lopes and Baudisch (2013). Only one report was identified that utilized monophasic rectangular pulses (Kurita et al., 2016).

The utilized pulse amplitude was mentioned in 8 out of 17 reports. Three reports used a current amplitude ranging from 10 mA to 27 mA (Kruijff et al., 2006; Lopes et al., 2017, 2018), one report limited the current up to 80 mA (Harris et al., 2016), two reports limited the current up to 100 mA (Lopes, Ion, et al., 2015; Lopes, Jonell, & Baudisch, 2015), and one report limited the current up to 150 mA (Galofaro et al., 2022). Notably, two reports defined the minimum and maximum current amplitudes through a calibration process (J. Lee et al., 2020; Lopes & Baudisch, 2013). The minimum current amplitude was established as the motor threshold—where observable muscle contractions occur—and the maximum current amplitude was identified as the self-reported PT of the user.

Table 3.1: EMS parameters used in the identified literature. Adapted from Vrontos et al. (2024), licensed under CC BY 4.0.

Parameter	**Value / Range**	**References**
Pulse Form	Biphasic	(Harris et al., 2016; Kruijff et al., 2006; J. Lee et al., 2020; Lopes, Ion, et al., 2015; Lopes & Baudisch, 2013)
	Monophasic Rectangular	(Kurita et al., 2016)
Pulse Amplitude	10 mA to 27 mA	(Kruijff et al., 2006; Lopes et al., 2017, 2018)
	Limited to 80 mA	(Harris et al., 2016)
	Limited to 100 mA	(Lopes, Ion, et al., 2015; Lopes, Jonell, & Baudisch, 2015)
	Limited to 150 mA	(Galofaro et al., 2022)
Pulse Width	25 μs to 45 μs	(Harris et al., 2016)
	Up to 60 μs	(Galofaro et al., 2022)
	70 μs to 200 μs	(Lopes et al., 2017)
	100 μs	(Khamis et al., 2019)
	100 μs to 420 μs	(Lopes et al., 2018)
	150 μs	(Lopes, Ion, et al., 2015)
	150 μs to 250 μs	(Lopes, Jonell, & Baudisch, 2015)
	260 μs	(Pfeiffer et al., 2013)
	290 μs	(Lopes & Baudisch, 2013)
	Up to 300 μs	(Harris et al., 2016)
	400 μs	(Kurita et al., 2016; J. Lee et al., 2020)
	500 μs	(Ishimaru & Saga, 2020)
	800 μs	(Ebisu et al., 2017)
Pulse Frequency	3 Hz to 5 Hz	(Kruijff et al., 2006)
	20 Hz to 40 Hz	(J. Lee et al., 2020)
	25 Hz	(Lopes & Baudisch, 2013)
	50 Hz	(Kurita et al., 2016)
	50 Hz to 70 Hz	(Ebisu et al., 2017; Pfeiffer et al., 2013)
	60 Hz	(Galofaro et al., 2022; Ishimaru & Saga, 2020)
	80 Hz to 140 Hz	(Lopes, Jonell, & Baudisch, 2015)
	100 Hz	(Khamis et al., 2019)
	120 Hz	(Lopes, Ion, et al., 2015)

The utilized pulse width was mentioned in 13 out of 17 reports. The values ranged between 25 μs and 800 μs. One study used a pulse width that varied between 1 μs and 60 μs (Galofaro et al., 2022). Seven reports used a pulse width less than 300 μs (Harris et al., 2016; Khamis et al., 2019; Lopes, Ion, et al., 2015; Lopes, Jonell, & Baudisch, 2015; Lopes & Baudisch, 2013; Lopes

et al., 2017; Pfeiffer et al., 2013), three reports used up to 420 μs (Kurita et al., 2016; J. Lee et al., 2020; Lopes et al., 2018), one report used up to 500 μs (Ishimaru & Saga, 2020), and one report used up to 800 μs (Ebisu et al., 2017).

The utilized pulse frequency was mentioned in 11 out of 17 reports. Pulse frequency in most reports was in the range from 20 Hz to 70 Hz (Ebisu et al., 2017; Galofaro et al., 2022; Ishimaru & Saga, 2020; Kurita et al., 2016; J. Lee et al., 2020; Lopes & Baudisch, 2013; Pfeiffer et al., 2013). The lowest pulse frequency was 5 Hz (Kruijff et al., 2006). Only two reports used a pulse frequency in the range between 100 Hz (Khamis et al., 2019) and 120 Hz (Lopes, Ion, et al., 2015). The highest reported frequency was found in Lopes, Jonell, and Baudisch (2015) with a value of 140 Hz.

To provide a clear comparison, these parameters have been grouped based on similarities in values found among the studies. These are outlined, along with their corresponding ranges, in Table 3.1.

3.3.3 Samples and Measures

The studies analyzed in this review exhibited significant variation in sample size, with the smallest study involving a group of four participants (Kurita et al., 2016), and the largest encompassing a group of 22 individuals (Khamis et al., 2019). The demographic profile of the samples predominantly featured male participants, as depicted in Fig. 3.2. In total, there were 83 male participants in total across all studies, compared to 30 female participants.

The participant base was relatively youthful, with average ages spanning from 22 to 31.2 years across various studies. For those studies that disclosed participant ages, we synthesized an approximation of the age distribution across all research. This age distribution is illustrated in Fig. 3.3.

Regarding the type of measures employed, the reviewed studies showcased a blend of objective and subjective techniques, with some adopting one or the other, and several employing a mix of both.

Objective measures, including force measurement (Galofaro et al., 2022; Ishimaru & Saga, 2020; Kurita et al., 2016; J. Lee et al., 2020; Lopes & Baudisch, 2013), angle measurement (Galofaro et al., 2022; Harris et al., 2016; Lopes,

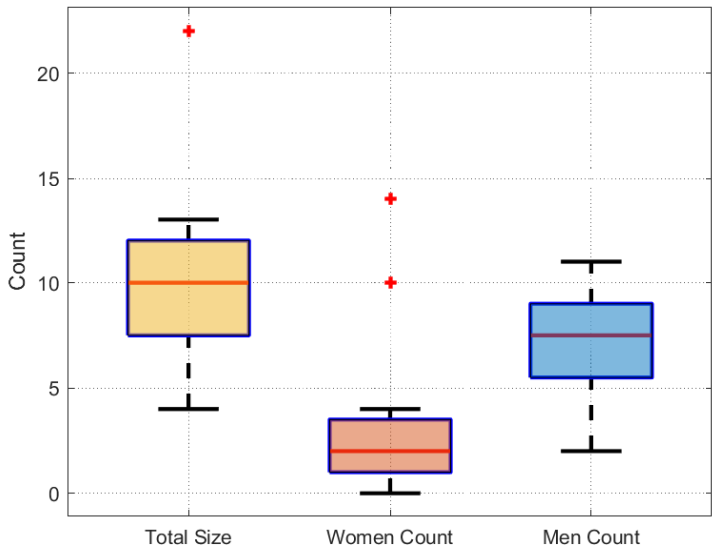


Figure 3.2: Boxplot of the sample sizes (Total, Women, and Men) for the $N = 12$ studies that reported participant sex distribution. The central red mark indicates the median sample size, while the bottom and top edges of the box represent the 25th and 75th percentiles, respectively. Reprinted from Vrontos et al. (2024), licensed under CC BY 4.0.

Ion, et al., 2015), time duration (Pfeiffer et al., 2019), and hand position (Ebisu et al., 2017) were used in nine of the studies to ascertain the physical implications of electrical stimulation.

Twelve studies used subjective measures like Likert scales, questionnaires, interviews (Ebisu et al., 2017; Faltaous et al., 2022; Galofaro et al., 2022; Ishimaru & Saga, 2020; Kruijff et al., 2006; Lopes, Ion, et al., 2015; Lopes, Jonell, & Baudisch, 2015; Lopes & Baudisch, 2013; Lopes et al., 2017, 2018; Pfeiffer et al., 2019) and the Igroup Presence Questionnaire (IPQ) (Khamis et al., 2019). Those were designed to capture the participants' personal perceptions and experiences. The use of Likert scales provided insights into participants' thoughts on various factors which among others include the intensity of the stimulation, the perceived weight, the realism of the simulated experience, their presence within the virtual environment, the consistency

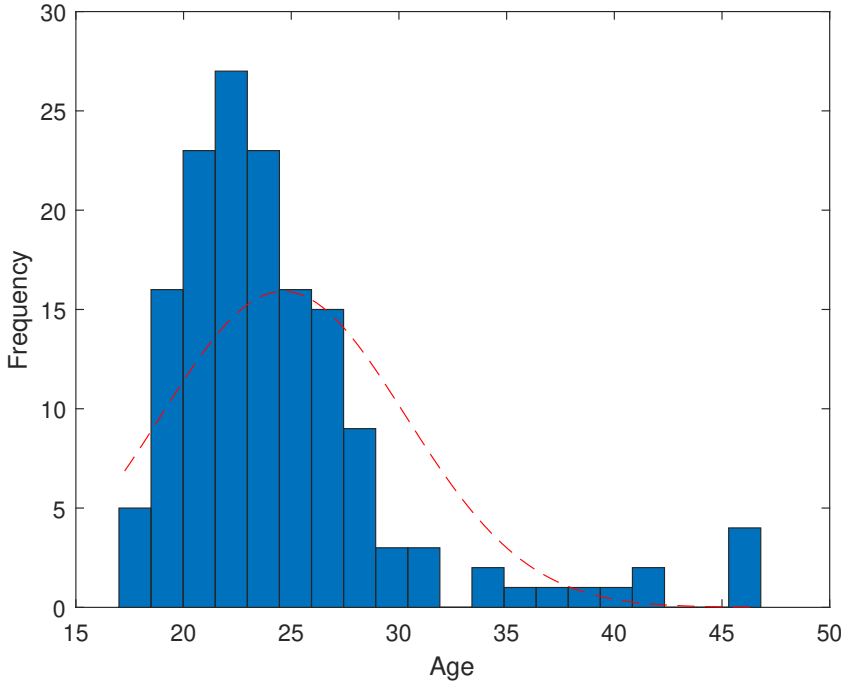


Figure 3.3: Approximated age distribution of all participants. Reprinted from Vrontos et al. (2024), licensed under CC BY 4.0.

and the naturalness of feedback, their enjoyment levels or pleasantness, comfort, and their personal preferences.

3.4 Identified Challenges and Research Gaps

While the systematic literature review confirms the growing interest in and potential of EMS for rendering kinesthetic feedback, it also reveals several critical challenges and research gaps that currently hinder the field's scientific progress. These issues primarily relate to a lack of methodological rigor in reporting, which impacts reproducibility, and a reliance on narrow demographic samples, which limits the generalizability of findings.

The most significant challenge identified is a pervasive inconsistency in the reporting of EMS parameters. Of the 17 studies reviewed, essential parameters were frequently omitted: only six detailed the pulse form, eight reported the pulse amplitude in milliamperes, eleven mentioned pulse frequency, and thirteen noted the pulse width. Critically, none

of the reviewed studies provided a complete description of all four essential parameters. This lack of comprehensive data poses a significant barrier to the replication of EMS studies, a fundamental requirement for scientific progress. This issue is further compounded by a severe lack of reporting on electrode specifics. Merely four papers included details about electrode size, and none provided a replicable description of the placement process. This points to an urgent need for the research community to collaboratively establish and adopt uniform reporting standards, ensuring that future studies provide comprehensive details on both EMS parameters and electrode configurations to guarantee the dependability of experimental results.

A second major gap lies in the demographic profile of the research participants. The findings show that the participant samples in the existing literature are predominantly young (mean ages between 22 and 31 years) and heavily skewed towards male participants (83 male vs. 30 female across all studies). This narrow demographic focus raises significant questions about the generalizability of the current findings. It remains unclear how these EMS techniques would be perceived by, or be effective for, a broader population, including women, older adults, or individuals with different body compositions and EMS thresholds. Addressing this limitation will require intentionally inclusive recruitment strategies in future research to ensure findings are truly representative and applicable to a wider audience.

In summary, the field of EMS for kinesthetic feedback is hampered by a lack of standardized reporting, which undermines reproducibility, and a reliance on homogeneous samples, which limits generalizability. These identified gaps form the primary motivation for the research presented in this thesis.

3.5 Implications for the Present Research

The systematic literature review reveals a promising but emerging field, limited by a lack of methodological consensus and a limited understanding of the factors that contribute to realistic and generalizable haptic experiences. The research presented in this thesis is directly motivated by these identified gaps and is structured as a multi-study investigation to systematically provide foundational knowledge, quantify moderating factors, and establish principles for multisensory integration.

The literature review revealed a fundamental ambiguity at the core of EMS haptic design: while early research demonstrated the feasibility of single-muscle EMS, the path toward achieving genuine realism remained unclear, with a clear lack of systematic, comparative data on different EMS strategies. To address this foundational gap, the

first empirical study of this thesis was designed as a comprehensive exploratory investigation. It provides the first systematic and quantitative comparison of single-muscle (triceps only) versus dual-muscle (triceps and forearm) EMS. By employing a multipart experimental design that captured not only the perceived magnitude of weight but also, critically, the subjective realism of the sensation, this study moves beyond mere feasibility. Its contribution is the establishment of clear, evidence-based support for a dual-muscle approach, providing a crucial and replicable baseline for future work in the field.

Beyond the EMS strategy itself, the review highlighted that the intricacies of EMS effects remain poorly understood, making a "one-size-fits-all" approach insufficient. This underscores that a rigorous quantitative model is not just a beneficial addition to the field but a necessity for progress. The second empirical study was designed as a foundational step in this direction, directly confronting the generalizability gap by quantifying the factors that mediate haptic perception. This work systematically examined how both ergonomic factors, such as the user's elbow angle, and intrinsic physiological characteristics, including age, BMI, and physical strength, influence the effectiveness and perceived realism of EMS feedback. By identifying a perceptual optimum for weight augmentation and demonstrating a significant correlation between user characteristics and perception, this study's primary contribution is a set of the first evidence-based guidelines for ergonomic and personalized haptic design, providing definitive proof that personalization is a necessity for effective EMS-based haptics.

Finally, while the reviewed literature establishes EMS as a potent haptic modality, it largely treats it in isolation, leaving a gap in our understanding of how EMS-based feedback integrates with other sensory inputs in a rich virtual environment. The third empirical study, therefore, aims to situate these haptic findings within the broader context of multimodal interaction by systematically investigating the principles of visuohaptic congruence. By employing a four-condition experimental design that isolates and combines visual and haptic feedback, this study measures the impact on both subjective perception (using the IPQ and custom scales for realism, visuohaptic mismatch, and sense of control) and objective user behavior (via kinematic analysis). The expected contribution is a set of clear, data-driven design principles for developers. These principles will guide the creation of more immersive and realistic virtual experiences by detailing how to synergistically combine EMS with visual rendering to enhance presence and, crucially, how to avoid the sensory conflicts that can shatter it.

4 Overall Research Methodology

4.1 Research Design and Paradigm

The research presented in this thesis is methodologically grounded in a post-positivist paradigm. This paradigm acknowledges that while a single, objective reality exists, it can only be apprehended imperfectly and probabilistically. It recognizes that the researcher's own biases and the limitations of experimental methods can influence outcomes. Therefore, this paradigm calls for a rigorous, empirical approach that emphasizes that scientific claims must be testable and capable of being proven wrong, and strives for objectivity through controlled experiments, replication, and critical evaluation. In alignment with this philosophy, the overall research approach is quantitative and experimental, designed to systematically test a priori hypotheses and establish causal relationships between manipulated variables—such as the number of stimulated muscles or the congruence of visuohaptic feedback—and their effects on user perception and behavior.

To systematically investigate the research questions, a multi-study experimental design was adopted. A within-subject (repeated measures) design was consistently employed across all three empirical studies. This methodological choice is particularly advantageous for perceptual and haptic research for several key reasons. First, it offers high statistical power by using each participant as their own baseline control, which effectively minimizes the error variance caused by the significant inter-individual differences in physiology, EMS thresholds, and subjective interpretation. Second, this design is more resource-efficient, typically requiring fewer participants than a between-subjects design to achieve the same level of statistical power.

The three studies were designed to follow a logical and cumulative progression. This structure allowed for a systematic inquiry that begins with foundational principles, proceeds to quantify moderating factors, and concludes by situating the findings within a realistic, multimodal application context. The progression is as follows:

- The first empirical study served a dual purpose. It began as an exploratory investigation to establish a foundational EMS technique, systematically comparing

single- versus dual-muscle EMS. It then used the collected data to develop and validate proof-of-concept ML models, demonstrating the feasibility of personalizing EMS feedback based on user-specific characteristics.

- The second empirical study built upon these findings with a parametric investigation to characterize the key factors that moderate EMS perception. It systematically examined the influence of ergonomic variables (elbow angle), augmentation parameters (base weight and magnitude), and intrinsic user characteristics. The study's primary contributions were to characterize the quantitative function mapping a target weight increase (in kg) to the required EMS intensity (in mA or %), demonstrate that posture is a critical factor for perceived realism, and establish the significant correlation between individual user characteristics and these perceptual outcomes.

- The third empirical study then integrated the established haptic principles into a multisensory context. Recognizing that haptic feedback in VR rarely occurs in isolation, this study used a 2x2 factorial design to investigate the principles of visuohaptic congruence. Its goal was to understand how EMS-based weight rendering interacts with congruent and incongruent visual feedback, providing data-driven design principles for creating cohesive and immersive virtual experiences.

4.2 Participant Recruitment, Demographics, and Ethical Considerations

The three empirical studies presented in this thesis involved a total of 146 experimental sessions. Participants for all studies were recruited from the local university and city community via informational flyers and postings. A standardized assessment procedure was used to ensure participant suitability and safety across the entire research program.

A common set of inclusion and exclusion criteria was applied. All participants were required to be between the ages of 18 and 64. To ensure participant well-being, a consistent set of exclusion criteria was adopted directly from the safety contraindications listed in the EMS device's user manual. These criteria included pregnancy, the presence of pacemakers, diagnosed or suspected heart conditions, skin diseases or open wounds at the intended EMS sites, and a history of epileptic seizures.

The three studies comprised distinct participant samples:

The first empirical study involved $N = 75$ participants (58 male, 17 female) with a mean age of 24.9 years ($SD = 3.4$). This sample size was determined by a power analysis conducted in G*Power for a linear multiple regression (fixed model, R^2 increase). The calculation was set to achieve a statistical power of 0.8 to detect a medium-to-large effect ($f^2 = 0.25$) with an α level of 0.05, assuming 11 total predictors. In this exploratory phase, a higher than standard effect size threshold ($f^2 = 0.15$) was chosen to prioritize the identification of robust, practically meaningful predictors for EMS calibration, filtering out minor effects that would lack utility for interface design.

The second empirical study involved $N = 35$ healthy volunteers (23 male, 12 female) with a mean age of 26.2 years ($SD = 4.36$). Its required sample size was determined through a power analysis simulation in Python. The simulation was configured for the study's repeated measures design to achieve a desired statistical power of 0.95 for a standard medium effect size (Cohen's $f = 0.25$) at an α level of 0.05.

The third empirical study involved $N = 36$ participants (24 male, 12 female), with a mean age of 23.5 years ($SD = 4.26$). This sample size was also determined by an a priori power analysis conducted in G*Power, specifically configured for a 2x2 repeated measures Analysis of Variance (ANOVA). The calculation was set to detect a significant interaction effect with a desired statistical power of 0.95 for a standard medium effect size (Cohen's $f = 0.25$) at an α level of 0.05.

Across all three studies, a standardized ethical protocol was followed. The research was conducted in accordance with the Declaration of Helsinki. The overarching experimental procedure received ethical approval from the Ethics Committee of the Medical Faculty of RWTH Aachen University (approval number: EK 23-210). Prior to participation, every individual received a thorough briefing on the experimental procedure, potential risks, and their right to withdraw at any time. Following this, all participants provided written informed consent. Participants in all studies were compensated for their time, receiving 30€ for the approximately two-hour sessions of the first two studies, and 15€ for the approximately one-hour session of the third study.

4.3 Apparatus and Materials

A consistent core experimental setup was used across all three empirical studies to ensure methodological reliability. The primary apparatus consisted of a computer-controlled, eight-channel EMS system (P24 Science, HASOMED© GmbH, Magdeburg, Germany), shown in Figure 4.1. This device was connected via USB to a Lenovo ThinkPad laptop (Windows 11, Core i5, 1.8 GHz, 16 GB RAM) running custom control software developed

in Python (see Appendix C for an illustrative example). This interface allowed for the real-time, dynamic adjustment of EMS parameters for the haptic rendering.

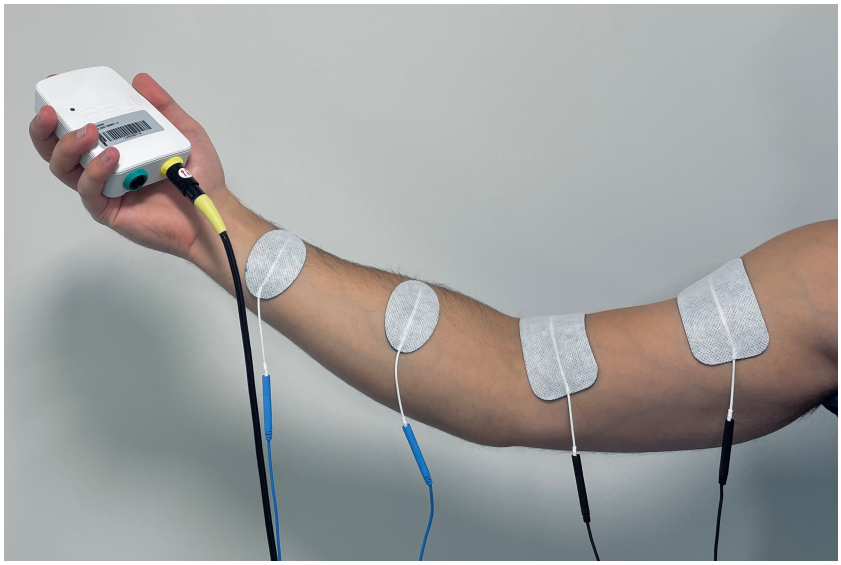


Figure 4.1: The P24 Science EMS system from HASOMED© (Magdeburg, Germany), illustrating its USB connection to a control PC and its application to the forearm and biceps muscles. This 8-channel device enables simultaneous EMS of up to eight target muscles, with EMS parameters dynamically controlled via external software. Reprinted from Vrontos et al. (2024), licensed under CC BY 4.0.

The EMS was delivered to the participant's dominant arm using self-adhesive, reusable electrodes (axion GmbH, Leonberg, Germany). The dominant arm was chosen for EMS because it is typically stronger and more resistant to the rapid onset of muscle fatigue that is characteristic of EMS, thereby ensuring a more stable and reliable perceptual response throughout the experimental trials. To maximize comfort and the efficiency of the EMS, the electrodes were placed near the MPs of each target muscle. The MPs were located using established anatomical visualizations from Hirai et al. (2021) and Behringer et al. (2014) for the triceps brachii, and from Abrams et al. (1997) for the extensor carpi ulnaris. Based on the target muscle group, two different sizes were consistently used: a 10x5 cm electrode for the triceps brachii and a 5x5 cm electrode for the extensor carpi ulnaris.

A set of standardized EMS parameters was used consistently across all studies to

ensure a reliable and comparable experience. The selection of these parameters was informed by the systematic literature review conducted for this thesis (Vrontos et al., 2024), with the detailed rationale for balancing effectiveness, comfort, and safety presented in the 'Technical Parameters and Best Practices' section (see Section 2.3.2). A symmetrical biphasic rectangular pulse was used, as this waveform is recommended to ensure comfort and eliminate residual electrical charge on the skin, thereby minimizing tissue irritation (Bowman & Baker, 1985; Diamant & Reilly, 2011; McNeal & Baker, 1988). The frequency was set to 40 Hz, a value high enough to produce a smooth, fused (tetanic) muscle contraction necessary for a continuous force sensation, yet low enough to mitigate the rapid onset of muscle fatigue (Behringer et al., 2016; Dreibati et al., 2010; Gorgey et al., 2009; Gregory et al., 2007; Knibbe et al., 2018; Peckham & Knutson, 2005). The pulse width was set to 120 µs, a duration found to provide a "neutral" sensation that avoids the uncomfortable tapping or pricking effects sometimes associated with other values (Bowman & Baker, 1985; Gracanin & Trnkoczy, 1975; Knibbe et al., 2018). With these parameters held constant, the intensity of the haptic sensation was exclusively controlled by modulating the current amplitude (mA), which was always personalized and constrained to each participant's individual dynamic range between their Motor and Pain Thresholds [MT, PT], as detailed in Section 4.4.2. Although the Sensory Threshold (ST) was also determined during the calibration, it served exclusively as a covariate for analysis and was not included in the calculation of this active dynamic range.

While this core haptic system remained constant, the specific physical and virtual materials varied to meet the distinct goals of each study:

- The first study utilized two physical weight plates (2 kg and 3 kg) for direct psychophysical comparison.
- The second study employed a larger set of five physical weights, including a Meta Quest 3 (MQ3) controller (0.15 kg) and four dumbbells (0.5 kg, 1 kg, 3 kg, and 5 kg), for its parametric investigation.
- The third study integrated the system with a full VR environment rendered on a MQ3 headset, using a physical 3 kg dumbbell with an attached MQ3 controller as the interactive virtual object.

A consistent suite of instruments was used to measure participant covariates across the studies, though the specific measurements were tailored to the goals of each investigation. While all studies recorded basic anthropometric data using a stadiometer for height and

a digital scale for weight, flexible tape measures were used to record upper arm length, forearm length, and upper arm circumference. The instrumentation for additional data collection varied. The first empirical study also utilized a multi-purpose scale to measure body composition—including fat, fluid, muscle, and bone mass percentages. In the second study, a digital goniometer was further utilized to set initial elbow angles and monitor for fatigue-induced drift. Additionally, the second and third empirical studies both employed a hand dynamometer to record maximum grip strength.

4.4 Data Collection Procedures

A standardized, multi-stage data collection protocol was employed across all three empirical studies to ensure consistency and methodological rigor. Each experimental session was structured to follow the same core sequence: a preparation and measurement phase, a personalized EMS calibration phase, and the main experimental task phase.

4.4.1 Participant Preparation and Covariate Measurement

Upon arrival at the laboratory, each participant was formally briefed in a personal discussion on the overall study purpose, the nature of the tasks to be performed, the sensations associated with EMS, and all safety procedures. They were given sufficient time to ask questions and were explicitly informed of their right to withdraw from the study at any point without penalty. Following this Q&A session, written informed consent was obtained from each participant. The complete Participant Information and Consent Forms for each of the three experiments can be seen in the appendix (see Appendices E.1, E.2, and E.3).

Subsequently, a comprehensive set of covariate data was collected. A core set of measurements was taken for all three studies; these were: demographic information (age, sex), handedness, and basic anthropometric data including height, weight, upper arm length (measured from the acromion to the olecranon), forearm length (measured from the olecranon to the styloid process of the ulna), and upper arm circumference. Additional, study-specific measurements were also recorded. For the first empirical study, these included body composition (fat, fluid, muscle, and bone mass percentages) using a smart weighting scale. The second and third empirical studies both included a measurement of maximum grip strength. Finally, the individual EMS thresholds (ST, MT, PT) determined during the subsequent calibration phase (see Section 4.4.2) were also recorded and treated as covariates.

The selection of these covariates was grounded in the physiological framework established in Chapter 2. The rationale for recording sex and body composition lies in findings that sex-based differences in electrical sensitivity are largely mediated by subcutaneous fat, which alters current diffusion and skin impedance (Maffiuletti et al., 2008; Seno et al., 2019), as described in Section 2.4. Age was included to account for known physiological declines in proprioceptive acuity and sensorimotor processing (Schaumburg et al., 2025). Anthropometric measures of the arm were included for biomechanical and physiological reasons: arm lengths determine the static moment—a primary driver of perceived heaviness (Mangalam et al., 2021)—while upper arm circumference serves as a proxy for muscle size, which directly influences the recruitment pattern and intrinsic response to EMS (Diamant & Reilly, 2011; Gregory & Bickel, 2005). Grip strength was recorded based on evidence that absolute strength is a significantly stronger predictor of haptic force control and steadiness than biological sex (Brown et al., 2010). Finally, the EMS thresholds were included to capture the significant inter-subject variability in pain and muscle activation limits that simple demographic adjustments cannot predict (Maffiuletti et al., 2008).

4.4.2 Standardized EMS Calibration Protocol

A crucial and consistent step in the procedure was the personalized calibration of the EMS device for each participant. This protocol was designed to establish each individual's unique and safe dynamic range for EMS. First, the skin on the dominant arm over the triceps brachii and extensor carpi ulnaris was prepared to ensure stable impedance and reliable signal transmission; this involved shaving (if necessary), cleaning with a disinfectant, and applying an electrode contact spray. Electrodes were then carefully placed near the estimated MP of each muscle, as detailed in Section 4.3, to maximize the efficiency of the muscle contraction while enhancing user comfort.

The calibration process then began, with the current amplitude for each muscle channel gradually increasing from 0 mA via a software-controlled ramp initiated by the experimenter at a constant rate of 0.5 mA/s. Three key thresholds were recorded:

- The ST, defined as the minimum EMS amplitude at which the participant first reported any sensation (e.g., a slight tingling).

- The MT, defined as the minimum EMS amplitude at which a small but clearly visible muscle twitch was observed by the experimenter.

- The PT, defined as the maximum EMS amplitude that the participant reported as being comfortable and not painful.

This procedure was performed separately and repeated twice for both muscles. The average values from these two measurements were then used to define the final thresholds, ensuring accuracy while minimizing pre-experiment fatigue. The resulting interval between the MT and PT, [MT, PT], established the personalized dynamic range used to normalize all EMS intensities during the main experiment, ensuring that the haptic feedback was effective, safe, and perceptually comparable across all participants. The ST was recorded for its potential use as a covariate and did not play a role in defining this dynamic range.

4.4.3 Core Experimental Procedure and Data Logging

While the specific independent and dependent variables differed across the three studies, the main experimental tasks followed a common paradigm and a consistent procedural sequence. All experiments began with a brief familiarization phase, where participants had the opportunity to handle the physical weights to be used in the study to ensure they could accurately register their feel.

Following this, the main experimental task began. In all studies, participants were seated upright on a chair with their shoulders in a neutral position. They were instructed to hold a physical weight or a controller-equipped object in their dominant hand while maintaining a specified posture, most commonly a 90° elbow flexion with a supinated wrist. During each experimental trial, EMS was programmatically applied to the antagonist muscles of the dominant arm—the triceps brachii and the extensor carpi ulnaris—to augment the perceived weight of the object. Participants were instructed to voluntarily activate their own muscles to counteract the EMS-induced torques and maintain a steady posture.

Data collection was centered around established psychophysical methods. The Method of Adjustment was a core technique used in the first two studies to quantitatively determine the PSE. As described by Treutwein (1995), this method involves varying the stimulus quasi-continuously until the subject perceives it to be equal to a standard reference. To minimize memory effects and capture immediate reactions, subjective data was collected immediately following each EMS event. This data was gathered via custom 7-point Likert scales to assess perceptual constructs like perceived realism and, where applicable, validated instruments such as the IPQ (see Appendix D for the specific questionnaires used in each study). In the third study, which involved a VR component,

objective kinematic data from the controller was also continuously recorded for behavioral analysis. To gather richer insights into the user's experience, qualitative feedback was gathered after the first two studies, while semi-structured interview was conducted at the end of the third experimental session. To mitigate the effects of muscular or cognitive fatigue, which is a known challenge with EMS, sufficient breaks (approximately 15 minutes) were provided between experimental blocks. Each session concluded with the removal of the electrodes, a full debriefing where participants could ask questions, and participant compensation.

4.5 Data Analysis Techniques

A consistent and rigorous data analysis pipeline was employed across the three empirical studies to process and interpret the collected data. All quantitative analyses were conducted using Python (v3.12) with its standard scientific libraries, including *scipy.stats*, *pandas*, *numpy*, *seaborn*, and *pingouin*. For all inferential statistical tests, the accepted Type I error significance level was set at $\alpha = 0.05$.

4.5.1 Inferential Statistical Analysis

The primary method for hypothesis testing involved comparing the dependent variables across the different experimental conditions. The specific statistical test used was chosen based on the data type and its distribution. For continuous or ordinal data, normality was first assessed using Shapiro-Wilk tests.

For data that met parametric assumptions, Repeated Measures ANOVAs were the primary analytical tool. The assumption of sphericity was checked using Mauchly's test, and a Greenhouse-Geisser correction was applied in cases where this assumption was violated. In the third study, a two-way repeated measures ANOVA was used to examine the main and interaction effects of the two independent variables (haptic and visual feedback). For any significant effects found in the ANOVAs, post-hoc pairwise comparisons were conducted using t-tests with a Bonferroni correction to control for multiple comparisons.

For continuous or ordinal data that was not normally distributed, the non-parametric Wilcoxon Signed-Rank test was used for comparing two related conditions (as the equivalent to a paired-samples t-test). For analyzing paired categorical data (e.g., shifts in 'increased'/'decreased'/'no change' responses), the McNemar-Bowker test was employed.

4.5.2 Correlational and Predictive Analysis

To investigate the influence of individual differences on the experimental outcomes, a consistent correlational approach was used. The relationships between participant covariates (e.g., age, BMI, strength) and the primary dependent variables (e.g., perceived realism, required EMS intensity) were analyzed using Pearson or Spearman correlation coefficients, depending on the data distribution.

Extending this predictive analysis, a ML approach was developed using the data from the first study. The goal was to create models capable of personalizing EMS amplitudes by predicting perceptual outcomes. The dataset, comprising participant characteristics and EMS data, was used to train and evaluate classification models. Several classifiers were compared, including Support Vector Classification (SVC), chosen for its effectiveness in high-dimensional spaces; Random Forest, an ensemble method that is robust to overfitting; and Extreme Gradient Boosting (XGBoost), a powerful and widely used algorithm known for its high performance on tabular data. A robust 5-fold cross-validation methodology was implemented, with participants grouped into folds to prevent data leakage, ensuring the models' performance was generalizable.

4.5.3 Qualitative Analysis

In addition to the quantitative analyses, qualitative data were collected across the studies to add depth and context to the findings, though the method of collection varied. For the first two empirical studies, informal qualitative feedback and participant comments were solicited post-experiment to gather general impressions. For the third study, a more formal approach was taken, and a semi-structured interview was conducted with each participant at the end of the session. The data from these semi-structured interviews were analyzed using a thematic analysis approach, where transcripts were systematically coded to identify key themes and extract representative quotes. In all cases, this qualitative data served to provide richer context and deeper interpretative insights into the quantitative findings, particularly concerning the participants' subjective experiences in each condition.

4.6 Validity, Reliability, and Generalizability Considerations

To ensure the scientific rigor of the research presented in this thesis, several measures were taken to maximize the validity and reliability of the experimental methods. This section details those measures and provides a critical consideration of the generalizability of the findings.

4.6.1 Internal Validity

Internal validity refers to the degree of confidence that the observed effects in the dependent variables were caused by the manipulation of the independent variables, rather than by extraneous factors. Several key design choices were implemented to strengthen internal validity:

- A within-subject design was consistently used across all three studies. By having each participant serve as their own baseline control, this design effectively eliminates confounding variables arising from pre-existing individual differences in physiology, strength, or sensory sensitivity.

- To mitigate potential order effects such as learning or fatigue, the presentation order of experimental conditions was counterbalanced for each participant. In the first two studies, this was achieved by randomizing the sequence of conditions. For the more complex 2x2 factorial design of the third study, a Latin Square was used to ensure a balanced presentation of the four conditions.

- To minimize the risk of demand characteristics (where participants might alter their behavior based on assumptions about the study's goals), participants in all studies were blinded to the specific hypotheses. This was achieved through the randomization or counterbalancing of conditions. This was particularly critical in the third study, where participants were also blind to the specific nature of the condition being presented at any given time.

- All experiments were conducted in a controlled laboratory setting with standardized instructions and procedures. This minimized the influence of environmental distractions and ensured that all participants experienced the tasks under comparable conditions.

4.6.2 Reliability

Reliability pertains to the consistency and replicability of the research methods and findings. The following protocols were established to ensure high reliability:

- A standardized, step-by-step protocol was followed for all experimental sessions, including participant briefing, informed consent, covariate measurement, skin preparation, electrode placement, and the main experimental tasks.
- The use of a specific, laboratory-grade EMS device (P24 Science, HASOMED© GmbH), controlled by custom Python software, ensured high hardware reliability. This setup provided direct, low-level control over all fundamental EMS parameters (e.g., pulse amplitude, width, and frequency), which is a crucial factor for the precise replication of the experimental conditions. Consistent measurement tools (e.g., hand dynamometer, goniometer) were also used to ensure the reliability of all recorded data.
- The most critical protocol for ensuring reliability was the individual calibration of each participant's ST, PT, and PT. By normalizing all subsequent EMS intensities as a percentage of this individual dynamic range [MT, PT], the perceptual effect of the EMS was made more consistent across participants, accounting for their unique physiological sensitivities.
- Subjective constructs were measured using custom-developed Likert scales across all studies, and for the third study, the validated and standardized IPQ was also employed.

4.6.3 External Validity and Generalizability

External validity, or generalizability, concerns the extent to which the findings of this research can be applied to other populations, settings, and contexts. While the controlled nature of the experiments strengthens internal validity, it also introduces certain limitations to generalizability that must be acknowledged.

The primary limitation concerns the participant sample. While the sample sizes (N=75, 35, and 36) are robust for within-subject haptic research, the demographic profile is consistent with the gap identified in the literature review: the participants were predominantly young, healthy university students. Therefore, caution must be exercised when generalizing these findings to other populations, such as older adults or individuals with different body compositions or sensory impairments.

A second consideration is ecological validity. The experiments were conducted in a controlled laboratory environment with a specific, focused task (holding a weight steady). The findings may not directly translate to more complex, dynamic, and distractor-rich scenarios typical of real-world VR applications. The trade-off between experimental control and ecological validity is a recognized aspect of this research paradigm.

Finally, the findings are specific to the muscles stimulated (triceps brachii and extensor carpi ulnaris) and the sensation rendered (weight). While the principles of personalization and visuohaptic congruence are likely applicable to other forms of EMS-based haptics, further research would be needed to confirm their generalizability to different muscle groups or haptic effects.

5 Empirical Study 1: From Foundational Principles to Personalization

5.1 Introduction to the Study

As established in the preceding literature review, EMS presents a compelling and practical alternative to bulky mechanical systems for rendering weight in virtual environments. However, its full potential is unrealized due to critical gaps in the existing research. The most significant of these is the lack of a systematic, quantitative comparison between different EMS strategies, with a particular focus on perceptual realism. While foundational studies have demonstrated the feasibility of single-muscle EMS, this approach has been qualitatively criticized as feeling unnatural. This highlights a clear need to investigate multi-muscle strategies that more closely align with the body's synergistic activation patterns.

This chapter presents the methodology and findings of a large-scale empirical study (N=75) designed to address this foundational gap. The rich dataset collected from this single, comprehensive experiment enables a unique two-part analysis that forms the structure of this chapter. Part A presents a fundamental, hypothesis-driven comparison of single- versus dual-muscle EMS, directly testing which strategy produces a stronger and, most importantly, more realistic weight sensation. Part B then utilizes the same dataset to take a novel, data-driven approach, developing ML models to explore the possibility of personalizing EMS feedback based on individual user characteristics. This chapter, therefore, moves from establishing a foundational haptic principle to exploring a next-generation approach for its application.

5.2 Part A: A Comparison of EMS Stimulation Strategies[1]

5.2.1 Objective and Hypotheses

While prior work has established the feasibility of using single-antagonist EMS to influence perceived weight (Faltaous et al., 2022; Galofaro et al., 2022), the literature reveals a critical gap: a lack of systematic, quantitative comparison between different EMS strategies, with a specific focus on perceptual realism. Foundational studies noted that while single-muscle EMS can generate force, the sensation was often perceived as unnatural, with participant feedback suggesting that the EMS of multiple muscle channels would be more realistic (Galofaro et al., 2022). This aligns with the physiological understanding that holding objects involves the coordinated effort of multiple muscles (Toma & Lacquaniti, 2016) and that forearm muscle activity is particularly crucial for heaviness perception (Waddell & Amazeen, 2017).

Therefore, the primary objective of this study was to conduct the first systematic, quantitative comparison between a single-muscle (triceps brachii) and a dual-muscle (triceps brachii and extensor carpi ulnaris) EMS strategy. The study was designed to determine not only which strategy elicits a greater change in the magnitude of perceived weight, but also, critically, which strategy enhances the subjective realism of the haptic sensation.

Based on the physiological principle established in Section 2.2.2 that weight perception is primarily derived from the sense of effort, and the understanding that natural object manipulation relies on the coordinated activation of multiple muscle groups (Section 2.4.4)—a factor identified in the systematic review (Section 3.3) as a key missing component in existing single-channel weight simulation studies—the following hypotheses were formulated:

[1] This section is based on the author's previously published, peer-reviewed article: Vrontos, A., Zolnouri, R., Mertens, A., Nitsch, V., & Brandl, C. (2025). Haptic Feedback for Interactive AR/VR Systems: Comparing Single- vs. Dual-Muscle EMS for Weight Perception. *Virtual Reality*. For this publication, the author of this thesis led the conceptualization, experimental design, data collection, analysis, and manuscript preparation. R. Zolnouri provided support during experimental execution and data analysis. Prof. Dr.-Ing. V. Nitsch, Prof. Dr.-Ing. A. Mertens, and Dr.-Ing. C. Brandl contributed through supervision, conceptual feedback, funding acquisition, and manuscript review. Specifically, Sections 5.2.1, 5.2.2, and 5.2.4 have been adapted and paraphrased for the context of this thesis, while Section 5.2.3 is reprinted verbatim. The original work is licensed under a Creative Commons Attribution 4.0 International License.

H1.1: EMS applied to antagonist muscles can simulate an increased weight sensation, making a held object feel heavier than its actual physical weight.

H1.2: The dual-muscle EMS condition is hypothesized to elicit a significantly greater increase in perceived weight compared to the single-muscle EMS condition.

H1.3: The dual-muscle EMS condition is hypothesized to be perceived as significantly more realistic than the single-muscle EMS condition.

5.2.2 Method

The study employed a within-subject experimental design, where each of the 75 participants (recruited and detailed in Section 4.2) was exposed to both EMS conditions across three distinct experimental parts. The core apparatus, described in Section 4.3, was used for stimulation; the specific materials for this study were physical weight plates of 2 kg and 3 kg.

Design and Independent Variable

The sole independent variable was the EMS Condition, with two levels:

- Single-Muscle EMS: EMS was applied only to the triceps brachii.
- Dual-Muscle EMS: EMS was applied simultaneously to the triceps brachii and the extensor carpi ulnaris.

The order in which participants experienced these two conditions was randomized across the three experimental parts to control for any potential order effects. A summary of the variables for each part is provided in Table 5.1.

Procedure

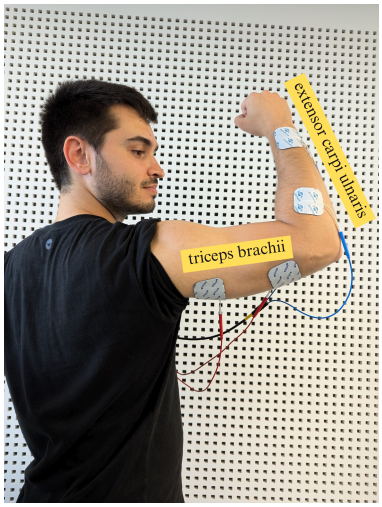
Each experimental session followed the standardized protocol for participant preparation and EMS calibration as detailed in the Overall Research Methodology chapter (see Section 4.4.2).

The main experimental task builds upon the core procedure described in Section 4.4.3. For this specific study, participants were seated upright, maintaining an elbow flexion of 90° and a supinated wrist. The experiment was divided into three distinct and sequential parts, with an approximately 15-minute rest period between each part to minimize muscle fatigue (see Figure 5.1 for an overview of the setup).

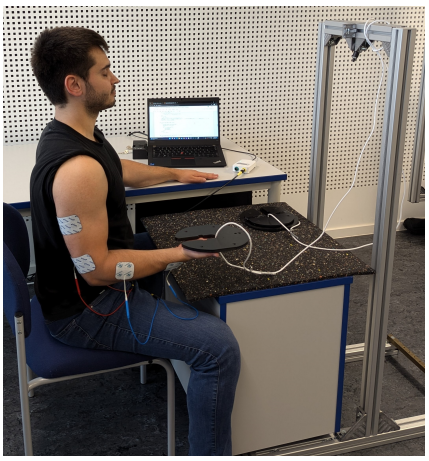
Table 5.1: Summary of independent and dependent variables, and EMS for each part. The terms 'motor threshold' and 'pain threshold', used within the 'EMS protocol' descriptions, are defined in detail in Section 4.4.2. Adapted from Vrontos, Zolnouri, Mertens, et al. (2025), licensed under CC BY 4.0.

	Independent variable	**Dependent variables**	**EMS protocol**
Part I	Condition: single-muscle EMS (triceps brachii) and dual-muscle EMS (triceps brachii and extensor carpi ulnaris)	•Perceived change in weight (7-point Likert scale) •Direction of weight change (increased, decreased, didn't change) •Perceived Realism of weight increase (7-point Likert scale)	EMS amplitude of triceps brachii and extensor carpi ulnaris (from MT to PT)
Part II	(same as in Part I)	•EMS amplitude at the PSE for triceps brachii - as percentage of range from MT to PT •EMS amplitude at the PSE for extensor carpi ulnaris - as percentage of range from MT to PT	EMS amplitude of triceps brachii and extensor carpi ulnaris (from MT to PT, or until the PSE is reached)
Part III	(same as in Part I)	Self-reported feedback on which side felt heavier (stimulated, non-stimulated, both equal)	EMS amplitude: nine randomized values (between MT to PT) for triceps brachii and extensor carpi ulnaris

Part I: Subjective Baseline Assessment In the first part, participants held a 2 kg weight. For each EMS condition, the EMS amplitude was linearly increased over 30 seconds from MT to PT. Immediately following this stimulus, participants completed a questionnaire (see Appendix D.1) to: (1) rate their certainty of a perceived change in weight on a 7-point Likert scale, (2) identify the direction of that change by selecting



(a) Placement of the electrodes on the triceps brachii and extensor carpi ulnaris of the dominant arm.



(b) Part I: Participant holding a 2 kg plate on their dominant hand with upright posture and eyes closed.



(c) Parts II and III: Participant holding a 2 kg plate on their dominant hand and a 3 kg plate on the other hand, with the same posture as in Part I.

Figure 5.1: Overview of the experimental setup and participant's posture in the three parts of the study. Reprinted from Vrontos, Zolnouri, Mertens, et al. (2025), licensed under CC BY 4.0.

from 'increased', 'decreased', or 'no change', and (3) rate the realism of the sensation on a 7-point Likert scale. Figure 5.2 illustrates this procedure.

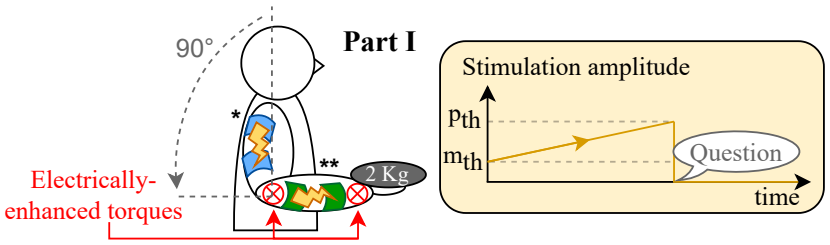


Figure 5.2: Illustration of the procedure for Part I: Subjective Baseline Assessment. Participants held a 2 kg weight while EMS intensity increased linearly, followed by questionnaire responses. **Note:* Although the figure depicts EMS on the right side, the dominant side of each participant was stimulated. ***Note:* Condition 1 involved stimulating only the triceps brachii; Condition 2 involved stimulating both the triceps brachii and the extensor carpi ulnaris. Reprinted from Vrontos, Zolnouri, Mertens, et al. (2025), licensed under CC BY 4.0.

Part II: Quantitative Comparison via PSE The second part employed the psychophysical Method of Adjustment. Participants held the 2 kg weight with EMS in their dominant hand and a 3 kg reference weight in their non-dominant hand. The EMS intensity was linearly increased from MT, and participants were instructed to verbally report "stop" at the precise moment they perceived the two weights to be equal, as shown in Figure 5.3. The primary dependent variable recorded was the EMS amplitude at this PSE.

Part III: Randomized Validation The final part used the same setup as Part II, illustrated in Figure 5.4. However, instead of a linear ramp, participants received nine short (6-second) EMS pulses at randomized, discrete intensity levels distributed across their [MT, PT] range. After each pulse, they made a trichotomous forced-choice response, verbally indicating which side felt heavier: the 'stimulated' side, the 'non-stimulated' side, or if both felt 'equal'. This part assessed perception under dynamic, non-linear EMS.

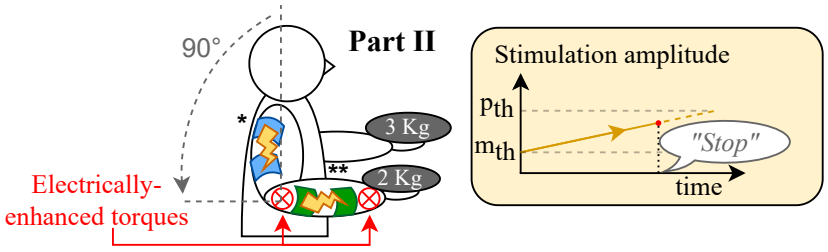


Figure 5.3: Illustration of the procedure for Part II: Quantitative Comparison via PSE (Method of Adjustment). Participants adjusted EMS intensity on the 2 kg weight (dominant hand) to match the perceived weight of the 3 kg reference (non-dominant hand). Reprinted from Vrontos, Zolnouri, Mertens, et al. (2025), licensed under CC BY 4.0.

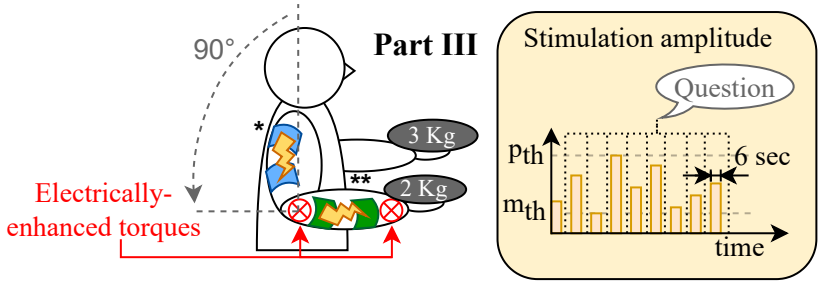


Figure 5.4: Illustration of the procedure for Part III: Randomized Validation (Forced-Choice Comparison). Using the same two-handed setup as Part II, participants compared weights after short, randomized EMS pulses. Reprinted from Vrontos, Zolnouri, Mertens, et al. (2025), licensed under CC BY 4.0.

5.2.3 Results[2]

The detailed statistical findings for each part of this study are presented below as they appear in the published work to ensure fidelity to the original analysis. The primary

[2]This section is reprinted verbatim from: Vrontos, A., Zolnouri, R., Mertens, A., Nitsch, V., & Brandl, C. (2025). Haptic Feedback for Interactive AR/VR Systems: Comparing Single- vs. Dual-Muscle EMS for Weight Perception. *Virtual Reality*. Open Access. This article is licensed under a Creative Commons Attribution 4.0 International License.

objectives of the analysis were to first confirm that EMS can effectively augment the perceived weight of a held object (H1.1), and then to test the main hypotheses that a dual-muscle EMS strategy would elicit a greater increase in perceived weight (H1.2) and be perceived as more realistic (H1.3) compared to a single-muscle approach. The results are presented sequentially for each of the three experimental parts. Due to the non-normal distribution of the subjective rating data, as indicated by Shapiro-Wilk tests, non-parametric statistical tests were primarily employed. In Part I, the realism item could only be answered by participants who actually perceived an increase in weight; the corresponding ratings therefore refer to the 55 participants who reported an increase under both conditions, as shown in Table 5.2.

Part I: Holding 2 kg and observing the effects of EMS on weight perception

Weight Change: A 7-point Likert scale was used (1: strongly disagree, 7: strongly agree) to assess if there was a change in the perceived weight sensation. Figure 5.5 displays the results, showing that the majority of participants reported an increase in the perceived weight of the 2 kg object due to EMS (Condition 1: 57 out of 75, or 76%; Condition 2: 73 out of 75, or 97%). Wilcoxon Signed-Rank tests indicate that participants rated their certainty of a perceived change in weight significantly higher for Condition 2 ($M = 6.01$, $SD = 0.94$) compared to Condition 1 ($M = 5.01$, $SD = 1.56$), $Z = -6.44$, $p < 0.001$, with a mean difference of 1.00 points and a medium to large effect size (Rank-Biserial $r = -0.74$).

Direction of Change: To assess changes in perceived weight direction ('increased', 'nothing', 'decreased') between Condition 1 and Condition 2, a McNemar-Bowker test (Bowker, 1948) was conducted. The results, displayed in Figure 5.6, show that most participants reported an increase in weight under both conditions. For those who changed their response, the sensation moved predominantly from 'decreased' to 'increased' or from 'nothing' to 'increased', indicating a stronger perception of weight increase in Condition 2.

The McNemar-Bowker test results were significant at $\alpha = .05$, χ^2 (df = 3, N = 75) = 14.31, $p = .0025$, indicating that the changes between categories were not symmetric. Examination of the 3x3 contingency table (Table 5.2)

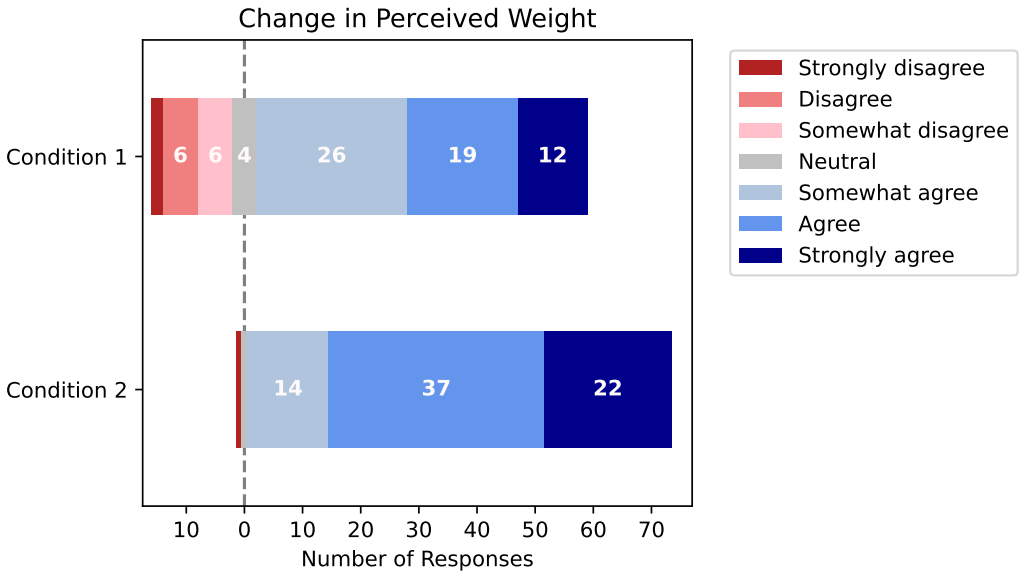


Figure 5.5: This figure displays the responses to the statement "I could feel a change in the perceived weight". The response "strongly agree" indicates that the weight of the object definitely changed, while the response "strongly disagree" indicates no change in the weight. Reprinted from Vrontos, Zolnouri, Mertens, et al. (2025), licensed under CC BY 4.0.

revealed that participants were more likely to report an increase in perceived weight in Condition 2 compared to Condition 1.

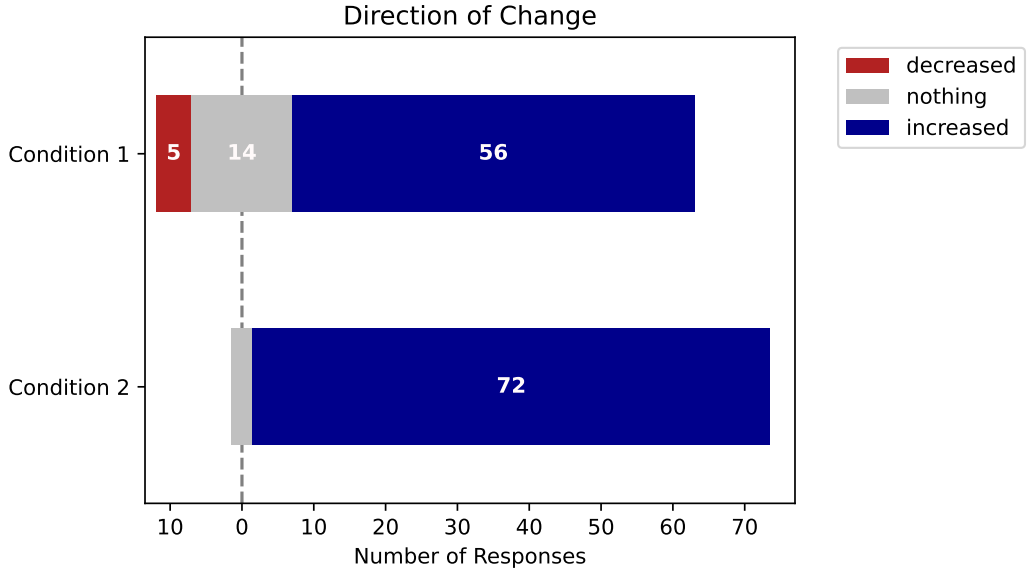


Figure 5.6: This figure displays how the participants responded when asked whether during the EMS the weight increased, decreased, or remained unchanged. Reprinted from Vrontos, Zolnouri, Mertens, et al. (2025), licensed under CC BY 4.0.

Realism: A 7-point Likert scale (1: strongly disagree, 7: strongly agree) was used to assess the realism of the increase in the perceived weight sensation. As shown in Figure 5.7, 28 out of 55 participants (51%) in Condition 1 and 41 out of 55 participants (75%) in Condition 2 somewhat to strongly agreed that the increases in weight felt as if they were caused by actual physical changes. Wilcoxon Signed-Rank tests revealed that participants rated the perceived realism significantly higher for Condition 2 ($M = 5.05$, $SD = 1.30$) compared to Condition 1 ($M = 4.20$, $SD = 1.38$), Z = -5.41, $p < 0.001$, with a mean difference of 0.85 points and a moderate effect size (Cohen's $d = 0.64$).

Condition 2	decreased	nothing	increased
Condition 1			
decreased	0	0	5
nothing	0	2	12
increased	0	1	55

Table 5.2: This contingency table shows how the responses of the participants changed between Condition 1 and 2, when asked about the direction of change in the weight sensation during Part I. Reprinted from Vrontos, Zolnouri, Mertens, et al. (2025), licensed under CC BY 4.0.

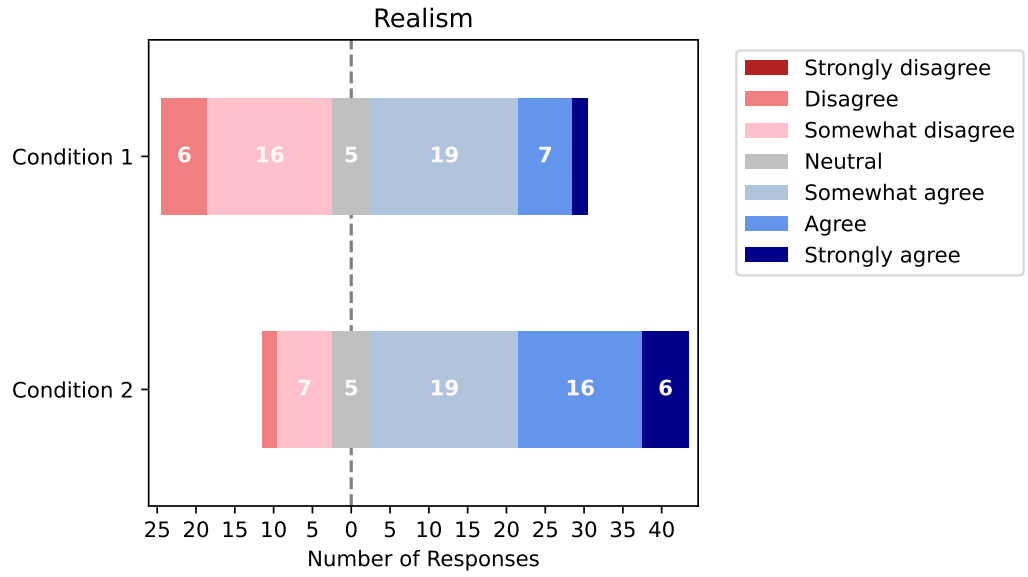


Figure 5.7: This figure displays how the participants responded to the statement "The increase in perceived weight felt natural, as if caused by a real, physical change". The response "strongly agree" indicates that the increase in the weight of the object felt very natural, while the response "strongly disagree" indicates that the increase in the weight of the object felt very artificial. Reprinted from Vrontos, Zolnouri, Mertens, et al. (2025), licensed under CC BY 4.0.

Part II: Comparing 2 kg with linear EMS in dominant hand against 3 kg in non-dominant hand

The stimulation amplitude increased linearly until participants perceived the 2 kg object as equal to a 3 kg object, reaching the PSE. The corresponding current amplitude (in mA) was then recorded and converted to a percentage, with 0% representing the participant's MT and 100% representing their PT. The results can be seen in Figure 5.8. Shapiro-Wilk tests indicated that the data for [Condition 1 were] not normally distributed (Condition 1: Statistic = 0.90, $p < 0.001$; Condition 2: Statistic = 0.97, $p = 0.099$). Therefore, Wilcoxon Signed-Rank tests were used for comparisons. The results showed that participants required significantly lower current amplitudes under Condition 2 ($M = 59.62$ %, $SD = 19.70$ %) compared to Condition 1 ($M = 77.15$ %, $SD = 20.22$ %), Z = -7.29, $p < 0.001$, with a mean difference of -17.53% and a large effect size (Cohen's d = -1.33). Additionally, three participants only reached the PSE under Condition 2, further supporting the hypothesis that Condition 2 results to a heavier weight perception than Condition 1.

Part III: Comparing 2 kg with randomized EMS in dominant hand against 3 kg in non-dominant hand

Participants provided oral feedback at each stimulation step, indicating which side felt heavier: the stimulated side (holding 2 kg), the non-stimulated side (holding 3 kg), or both sides felt same heavy (PSE). This feedback was collected for each of the nine random stimulation intensities applied during both Condition 1 (stimulate only the triceps) and Condition 2 (stimulate both the triceps and lower arm). The distribution of the results for the two conditions can be seen in Figure 5.9. The mean differences in responses between Condition 1 and Condition 2 were -5.89% for "non-stimulated", -11.77% for "same" and -5.74% for "stimulated".

The McNemar-Bowker test results were significant at $\alpha = .05$, χ^2 (df = 3, N = 75) = 112.00, $p < .001$, indicating a significant difference between Condition 1 and Condition 2. Examination of the 3x3 contingency table (Table 5.3) revealed that participants were more likely to report a perceived increase in weight under the randomized EMS pattern in Condition 2 compared to Condition 1.

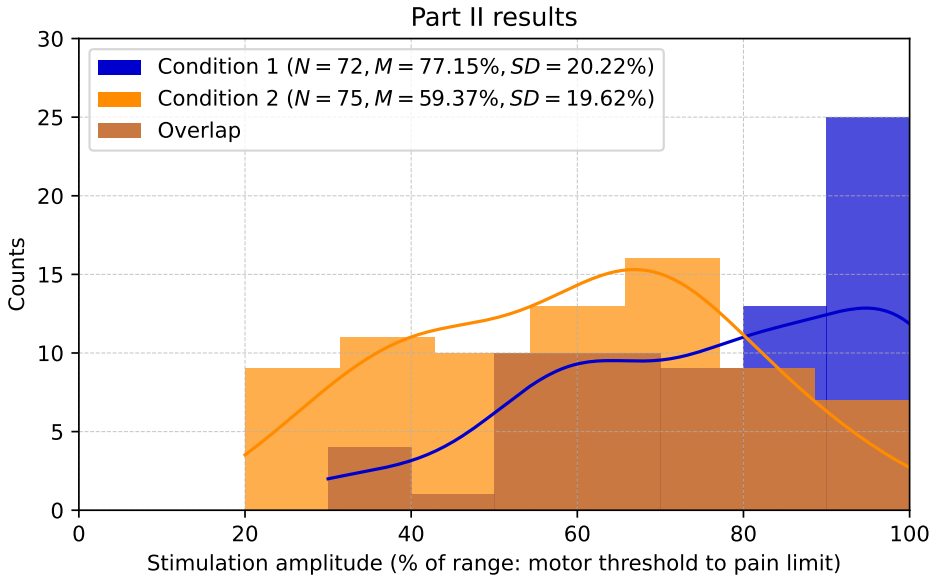


Figure 5.8: This figure shows the distribution of the PSEs—the EMS amplitude at which the 2 kg object felt as heavy as the 3 kg object. The distributions are displayed for Condition 1 (blue) and Condition 2 (orange). The legend reports all available cases per condition; the Wilcoxon test reported in the text is based on the 72 participants who reached the PSE in both conditions. Adapted from Vrontos, Zolnouri, Mertens, et al. (2025), licensed under CC BY 4.0.

For each participant, the proportion of times the stimulated side felt heavier was calculated for both conditions. These proportions were then compared across all participants using a Wilcoxon Signed-Rank test. The results indicated a significant difference between the two conditions, $W = 68.50$, $p < .001$, at $\alpha = .05$. Specifically, participants reported a higher proportion of instances where the stimulated side (2 kg) felt heavier than the non-stimulated side (3 kg) under Condition 2 compared to Condition 1, supporting the hypothesis that stimulating both the triceps and lower arm leads to a greater perceived weight sensation than stimulating only the triceps.

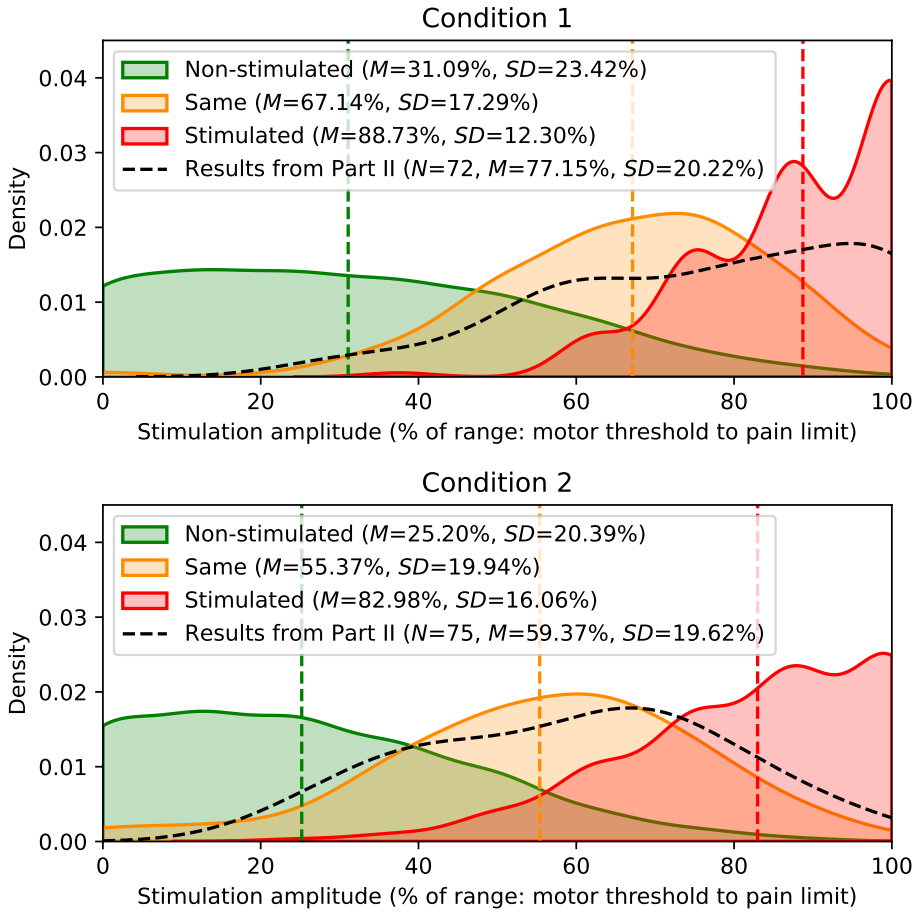


Figure 5.9: This figure shows the distribution of participants' responses in Part III, with Condition 1 (top) and Condition 2 (bottom). Adapted from Vrontos, Zolnouri, Mertens, et al. (2025), licensed under CC BY 4.0.

Condition 2	Non-stimulated	Same	Stimulated
Condition 1			
Non-stimulated	328	63	28
Same	5	42	46
Stimulated	1	3	159

Table 5.3: This contingency table shows how the responses of the participants changed between Condition 1 and 2, during Part III. Reprinted from Vrontos, Zolnouri, Mertens, et al. (2025), licensed under CC BY 4.0.

5.2.4 Discussion of Part A

The results provide strong empirical support for all guiding hypotheses. First, the foundational premise of the study (H1.1) was clearly confirmed: EMS can effectively augment the perceived weight of a held object. The vast majority of participants in both the single-muscle (76%) and dual-muscle (97%) conditions reported that the object felt heavier during EMS, validating the core principle of using antagonist EMS to simulate weight, in line with prior work (Faltaous et al., 2022; Galofaro et al., 2022; Lopes et al., 2017, 2018).

Beyond this baseline confirmation, the findings demonstrate that a dual-muscle EMS strategy is significantly superior to a single-muscle approach. Across all measures, the dual-muscle condition elicited a greater increase in perceived weight (H1.2) and was rated as substantially more realistic (H1.3). This superiority was consistent across the three distinct experimental parts, highlighting the robustness of the finding. The subjective ratings from Part I established that participants felt a stronger and more natural sensation when the forearm was included; indeed, for 16% of participants, the single-muscle EMS was not sufficient to elicit a feeling of increased weight at all. The quantitative PSE measurements from Part II provided objective evidence that this dual-muscle strategy was also more efficient, requiring significantly less current—a mean difference of 17.53% of the participants' dynamic range—to simulate the same 1 kg increase in weight. Theoretically, this efficiency suggests that, as described in Section 2.2, the brain integrates the combined afferent "population code" from multiple muscles to form a holistic percept, rather than relying on a single channel (Proske & Gandevia, 2012). Finally, the validation in Part III confirmed that this perceptual advantage holds even for dynamic, randomized EMS that are more representative of real-world haptic events.

These findings provide the first quantitative validation for the qualitative feedback re-

ported in earlier foundational studies, where participants noted that single-muscle EMS felt unnatural (Galofaro et al., 2022)—directly addressing the lack of systematic comparison between actuation strategies identified in the systematic review (Section 3.4). The enhanced perceived realism of the dual-muscle condition is likely because it more closely mimics the body's natural biomechanics. Human weight perception is a whole-arm phenomenon, and by engaging the extensor carpi ulnaris, the EMS provides feedback not just at the elbow but also at the wrist. This aligns with foundational work establishing that global muscle activity explains the majority of force perception variance (Toma & Lacquaniti, 2016) and underscores the importance of forearm muscle activity and wrist inertia in how humans perceive heaviness (Waddell & Amazeen, 2017). While the dual-muscle sensation was rated as significantly more realistic ($M = 5.05$ out of 7), qualitative feedback from participants highlighted that sensations of tingling or muscle twitching could sometimes detract from the experience. Physiologically, these artifacts are likely consequences of the inverted recruitment pattern typical of surface EMS, where larger, fast-twitch fibers are activated before fatigue-resistant ones (Diamant & Reilly, 2011; Gregory & Bickel, 2005). This aligns with findings from Lopes et al. (2017) that EMS can draw "undesired attention"; as noted in Section 2.1, such ambiguous sensations risk breaking the user's immersion by shifting attention from the virtual interaction to the physical interface (Gao & Spence, 2025).

While this study establishes a foundational EMS strategy, a key challenge remains unaddressed. The results, particularly the outliers and the qualitative feedback on comfort, highlight the significant inter-subject variability in how users perceive EMS, likely driven by intrinsic differences in muscle fiber composition and skin impedance (Seno et al., 2019). Establishing that a dual-muscle approach is superior answers the question of what technique to use, but it does not address the question of how to apply it effectively for each individual. This naturally leads to the next phase of this investigation: moving beyond a simple comparison and exploring a data-driven method for personalization.

5.3 Part B: A Machine Learning Approach to Personalization[3]

5.3.1 Objective and Hypotheses

Building on the findings from Part A, the second part of this study addresses the critical challenge of inter-subject variability in EMS-based haptics. While the previous analysis established a superior EMS technique, a key challenge remains in determining the precise EMS amplitude required for each individual to perceive a specific weight increase. As the systematic review of the field has shown, existing studies establish the effectiveness of EMS but do not offer a systematic solution for personalizing EMS parameters for different individuals—an essential step for ensuring consistent proprioceptive feedback (Vrontos et al., 2024). This variability stems from a range of factors including individual physical characteristics and personal EMS thresholds. Manually tuning these parameters for each user is impractical and not scalable.

As established in the theoretical background (see Section 2.5.2), a data-driven, ML-based approach is a fundamental technology for moving beyond static parameters and making reliable predictions from complex, high-dimensional user data (Rajkomar et al., 2019; Sidey-Gibbons & Sidey-Gibbons, 2019).

This approach is strongly supported by ML's proven efficacy in other bio-feedback-controlled EMS contexts, where it is used to create personalized and adaptive therapies. In these systems, a closed-loop is formed where real-time bio-feedback from EMG sensors, which measure a user's muscle response, serves as the input for an ML model. The model then processes this data to dynamically adjust EMS parameters based on the individual's specific physiological state, optimizing the intervention in real-time (Ghosn, 2023). This demonstrated capacity makes ML a powerful paradigm for modeling the complex, non-linear relationships between user characteristics and perceptual outcomes

[3] © 2025 IEEE. Reprinted, with permission, from: Vrontos, A., Zolnouri, R., Nitsch, V., Mertens, A., & Brandl, C. (2025). Personalized Electrical Muscle Stimulation for Precise Weight Perception in Virtual Reality: A Machine Learning Approach. *2025 IEEE International Conference on Systems, Man, and Cybernetics*. For this publication, the author of this thesis conceptualized and designed the experiment, performed the majority of the experimental work, carried out data cleaning and initial data analysis, and drafted major portions of the manuscript. R. Zolnouri supported experiment execution, led the machine learning analysis, contributed to interpreting results, and wrote parts of the manuscript. Prof. Dr.-Ing. V. Nitsch, Prof. Dr.-Ing. A. Mertens, and Dr.-Ing. C. Brandl provided supervision, conceptual guidance, funding acquisition, and contributed to the review and editing of the manuscript. Specifically, Sections 5.3.1, 5.3.2, and 5.3.4 have been adapted and paraphrased for the context of this thesis, while Section 5.3.3 is reprinted verbatim.

in haptics.

The primary objective of this investigation was therefore to develop and evaluate ML models capable of personalizing EMS feedback. The goal was to leverage the rich dataset collected in this study to create models that could predict the perceptual outcome of a given EMS amplitude for a specific individual, and to identify the hierarchy of the most important features driving these predictions. These models were trained to classify whether a 2 kg object, augmented with a specific EMS intensity, would be perceived as lighter than, equal to, or heavier than a 3 kg reference weight.

Driven by the potential of ML to decipher complex, non-linear sensorimotor mappings as described in Section 2.5.2, and the necessity to account for the significant physiological variability—such as body composition and sensitivity thresholds—identified in Section 2.4.2, this predictive approach was guided by the following hypotheses:

H1.4: A ML model can be trained to reliably predict the perceived weight difference (lighter, equal, or heavier) from user-specific features and the applied EMS amplitude, achieving a classification accuracy significantly greater than chance.

H1.5: While the applied EMS amplitude will be a primary predictor, a combination of individual user characteristics—specifically personal EMS thresholds (motor and pain), anthropometric data (e.g., BMI), and physical attributes—will be significant features that improve the model's predictive performance.

5.3.2 Method

The ML analysis presented in this part is based on the dataset collected from the 75-participant experiment detailed in Part A. The general participant information, apparatus, and standardized procedures—including the crucial EMS calibration protocol—are detailed in the 'Overall Research Methodology' chapter (Chapter 4). This section focuses exclusively on the methods specific to the construction of the dataset and the development and evaluation of the predictive models.

Dataset, Features, and Target Variable

The dataset was constructed from the 675 trials (75 participants × 9 randomized EMS amplitudes) generated in Part III of the foundational experiment. During this data collection task, participants were seated upright and held a 2 kg plate in their dominant hand (the stimulated arm side) and a 3 kg plate in their non-dominant hand, as depicted

in Figure 5.10. For each of the nine randomized EMS steps, participants provided a self-reported response indicating which side felt heavier. Each of these responses constitutes a single instance in the dataset.

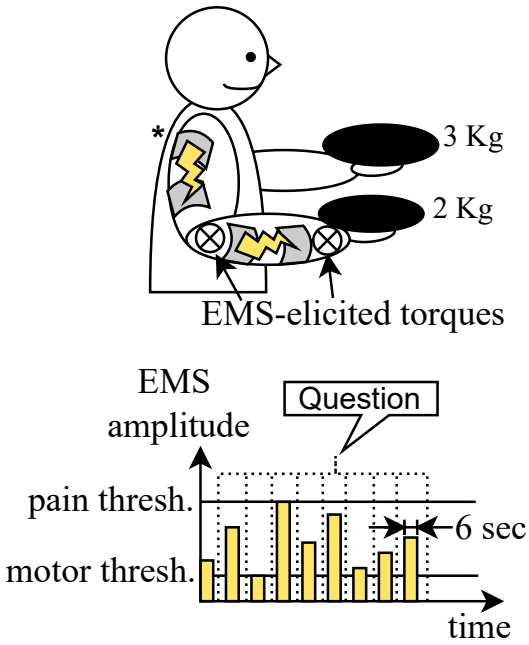


Figure 5.10: Illustration of the experimental setup for the data collection task in Part B. © 2025 IEEE. Reprinted, with permission, from Vrontos, Zolnouri, Nitsch, et al. (2025).

The target variable (ℓ) for the classification task was the participant's trichotomous response after each stimulus, categorized as: (0) the non-stimulated side (3 kg) felt heavier, (1) both sides felt equally heavy, or (2) the stimulated side (2 kg + EMS) felt heavier.

The predictor variables (features) for each instance were composed of the dynamic EMS amplitude applied to the triceps during that trial, along with a static set of user-specific features measured prior to the experiment. These features included:

- Demographic characteristics: Age and sex.
- Physical characteristics: Dominant arm, weight, height, BMI, body fat percentage,

body fluid percentage, muscle mass percentage, bone mass, maximum triceps force, upper arm length, forearm length, and upper arm circumference.

- Individual EMS Thresholds: The individually calibrated STs, MTs, and PTs for both the triceps brachii and extensor carpi ulnaris.

EMS Amplitudes and Model Evaluation

For each participant s, the MT and PT were individually calibrated for both the extensor carpi ulnari ($a^{e,s}$, $A^{e,s}$) and the triceps brachii ($a^{t,s}$, $A^{t,s}$). All EMS amplitudes were discretized to 0.5 mA increments, reflecting the technical limits of the device.

A set of nine distinct EMS amplitude levels $\{a_i^{t,s} \mid 1 \leq i \leq 9\}$ was defined for the triceps brachii, with the values evenly spaced between the participant's measured MT ($a^{t,s}$) and PT ($A^{t,s}$). To prevent sequence-related bias, these nine levels were presented in a randomized order, as described in Equation 5.1.

$$a_i^{t,s} \sim \text{Uniform}\Big(\{a_1^{t,s}, \ldots, a_9^{t,s}\} \setminus \{a_1^{t,s}, \ldots, a_{i-1}^{t,s}\}\Big). \tag{5.1}$$

For each triceps EMS amplitude, a corresponding EMS amplitude for the extensor carpi ulnaris ($a_i^{e,s}$) was computed using a linear mapping. This procedure, shown in Equation 5.2, ensured that the EMS amplitude for the second muscle maintained the same relative position within its own [MT, PT] dynamic range.

$$a_i^{e,s} = a^{e,s} + \frac{a_i^{t,s} - a^{t,s}}{A^{t,s} - a^{t,s}} \cdot (A^{e,s} - a^{e,s}) \tag{5.2}$$

where $1 \leq i \leq 9$.

Both values in the resulting amplitude pair $(a_i^{t,s}, a_i^{e,s})$ were rounded to the nearest 0.5 mA. Participants experienced all nine paired EMS amplitudes in the randomized order, and their perceptual response (which side felt heavier, resulting in a label $\ell_i \in \{0, 1, 2\}$) was recorded for each trial.

This process generated nine distinct data instances for each of the 75 participants. Each instance was composed of the 14 static features for that subject (M_s, detailed in Section 5.3.2), the applied triceps EMS amplitude ($a_i^{t,s}$), and the recorded perceptual label (ℓ_i).

To evaluate model performance, a 5-fold cross-validation was implemented. The 75 participants were randomly divided into 5 distinct groups. For each fold, 15 participants (135 instances) served as the test set, while the remaining 60 participants (540 instances)

were used for training. This participant-based splitting strategy is essential to prevent data leakage, ensuring that the model is validated on its ability to generalize to new, unseen users. The final performance was calculated by averaging the results across all five folds.

Model performance was quantified using four standard classification metrics. Accuracy was calculated as the overall proportion of correct predictions. For Precision, Recall, and F1-Score, a weighted average strategy was employed to account for potential class imbalances. This means that the metric was first calculated for each class individually and then averaged, with each class's contribution weighted by its support (the number of true instances for that class). These metrics are defined as:

$$\text{Accuracy} = \frac{\text{Total Correct Predictions}}{\text{Total Number of Samples}} \tag{5.3}$$

$$\text{Precision} = \sum_{c \in Classes} w_c \cdot \frac{TP_c}{TP_c + FP_c} \tag{5.4}$$

$$\text{Recall} = \sum_{c \in Classes} w_c \cdot \frac{TP_c}{TP_c + FN_c} \tag{5.5}$$

$$\text{F1-Score} = \sum_{c \in Classes} w_c \cdot \left(2 \cdot \frac{\text{Precision}_c \cdot \text{Recall}_c}{\text{Precision}_c + \text{Recall}_c} \right) \tag{5.6}$$

where w_c represents the proportion of samples belonging to class c in the dataset. The final performance values reported in the Results section represent the mean of these weighted metrics across all five cross-validation folds.

Additionally, to enable an assessment of performance in terms of Signal Detection Theory, the specific counts of Hits (True Positives), Misses (False Negatives), False Alarms (False Positives), and Correct Rejections (True Negatives) can be derived directly from the confusion matrices presented in the Results section.

5.3.3 Results[4]

To ensure accuracy and fidelity to the original publication, the following results are reprinted verbatim from the author's peer-reviewed conference paper.

[4] © 2025 IEEE. This section is reprinted verbatim, with permission, from: Vrontos, A., Zolnouri, R., Nitsch, V., Mertens, A., & Brandl, C. (2025). Personalized Electrical Muscle Stimulation for Precise Weight Perception in Virtual Reality: A Machine Learning Approach. *2025 IEEE International Conference on Systems, Man, and Cybernetics.*

Feature Selection

A backward feature elimination strategy was employed using an SVC classifier to enhance model interpretability and performance. This iterative process systematically removed the least influential features based on their impact on test accuracy, continuing until the feature set was reduced to six key predictors: EMS amplitude applied to the triceps brachii, Triceps brachii muscle PT, Triceps brachii muscle MT, Extensor carpi ulnaris PT, BMI, and Forearm length.

These selected features constituted the final dataset for model training. Although age and sex were initially considered as potential predictors, their low variability rendered them uninformative for model training. Consequently, these features were excluded to avoid redundancy and unnecessary complexity. All machine learning models were implemented using the scikit-learn library in Python, with the random seed set to 0 for reproducibility, and hyperparameters for each classifier were optimized using the Optuna library.

Model Performance

We trained three classifiers—SVC, Random Forest, and XGBoost—over five cross-validation iterations. These models were selected based on their empirically demonstrated performance on tabular datasets. SVC is effective in high-dimensional spaces, Random Forest utilizes ensemble learning to reduce variance, and XGBoost leverages gradient boosting to achieve superior predictive accuracy. Table 5.4 presents the average performance metrics. Notably, XGBoost achieved the highest accuracy (77%), accompanied by matching precision and recall (77%), resulting in an F1-score of 77%. Random Forest also attained a balanced profile, with an accuracy of 74%, while SVC exhibited an accuracy of 72%.

To provide a more detailed view of each classifier's performance, Figure 5.11 presents the confusion matrices for SVC, Random Forest, and XGBoost, aggregated across the five cross-validation folds. These matrices illustrate the number of correctly classified instances for each class (0, 1, and 2) and the extent of misclassifications. Among the models, XGBoost demonstrates the most balanced distribution of correct predictions across all classes, highlighting its robustness.

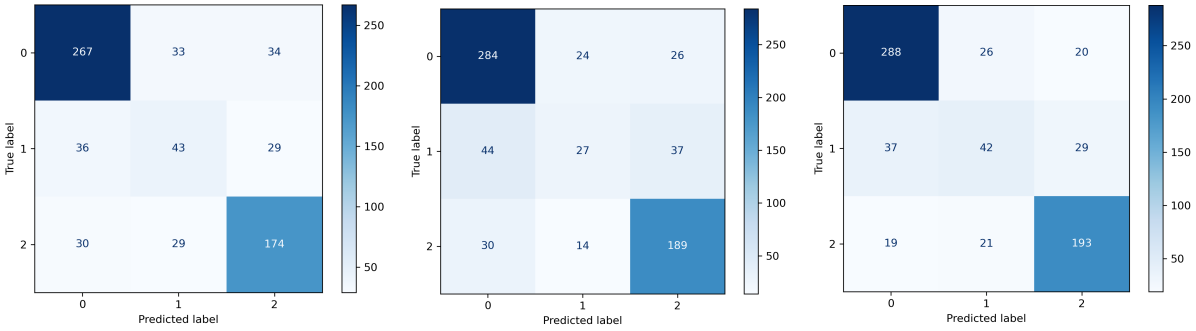
Table 5.4: Performance metrics for the ML models. © 2025 IEEE. Reprinted, with permission, from Vrontos, Zolnouri, Nitsch, et al. (2025).

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
SVC	72%	73%	72%	72%
Random Forest	74%	73%	74%	73%
XGBoost	77%	77%	77%	77%

Focusing first on the SVC model, it performs well in predicting class 0, with 267 correct predictions, though it misclassifies 33 instances as class 1 and 34 as class 2. Similarly, class 2 is correctly predicted in 174 cases, but 30 instances are misclassified as class 0 and 29 as class 1. The greatest challenge for SVC lies with class 1, where only 43 instances are correctly classified, while 36 are misclassified as class 0 and 29 as class 2. These results indicate that the SVC struggles particularly with distinguishing class 1 from the other two classes.

The Random Forest classifier shows improved performance compared to the SVC. It achieves 284 correct predictions for class 0, with fewer misclassifications into class 1 (24) and class 2 (26). For class 2, the model correctly predicts 189 instances, misclassifying only 30 as class 0 and 14 as class 1. However, the performance for class 1 remains a challenge, with only 27 correct predictions, while 44 instances are misclassified as class 0 and 37 as class 2. Despite this, the Random Forest demonstrates a more balanced performance for classes 0 and 2, albeit still struggling with class 1.

Finally, the XGBoost model exhibits the best performance among the three classifiers. It achieves 288 correct predictions for class 0, with only 26 and 20 instances misclassified as Classes 1 and 2, respectively. For class 2, XGBoost correctly predicts 193 instances, with minimal misclassifications into class 0 (19) and class 1 (21). The performance for class 1 also shows improvement, with 42 correct predictions and fewer misclassifications into class 0 (37) and class 2 (29). Overall, XGBoost demonstrates the most balanced performance across all three classes, with higher accuracy and fewer errors compared to the other models.



(a) SVC (b) Random Forest (c) XGBoost

Figure 5.11: Overall confusion matrices for the models using 5-fold cross-validation. © 2025 IEEE. Reprinted, with permission, from Vrontos, Zolnouri, Nitsch, et al. (2025).

Feature Analysis

To better understand the influence of the selected features and to diagnose potential multicollinearity, a more detailed feature analysis was conducted. We used the best-performing XGBoost model to quantify feature contributions, as its importance scores provide a robust measure of each predictor's impact on the model's decisions.

Feature importance scores were calculated using this model (Fig. 5.12). The analysis revealed that EMS Amplitude was by far the most influential feature, followed by the participant's BMI and Triceps PT. This highlights that the applied stimulation and key individual anthropometric and physiological traits are the primary drivers of perception.

Furthermore, to specifically diagnose the extent of multicollinearity, a Pearson correlation matrix was computed (Fig. 5.13). This analysis helps clarify the relationships between predictors and assesses the potential for feature redundancy. The matrix shows a moderate positive correlation between the Triceps PT and Extensor Carpi PT ($r = 0.62$), and also between EMS Amplitude and the triceps thresholds ($r = 0.50$ to 0.60). Physical characteristics like BMI and Forearm Length showed low correlation with other features, indicating they provide unique information to the model. The implications of these correlations are addressed in the Discussion section.

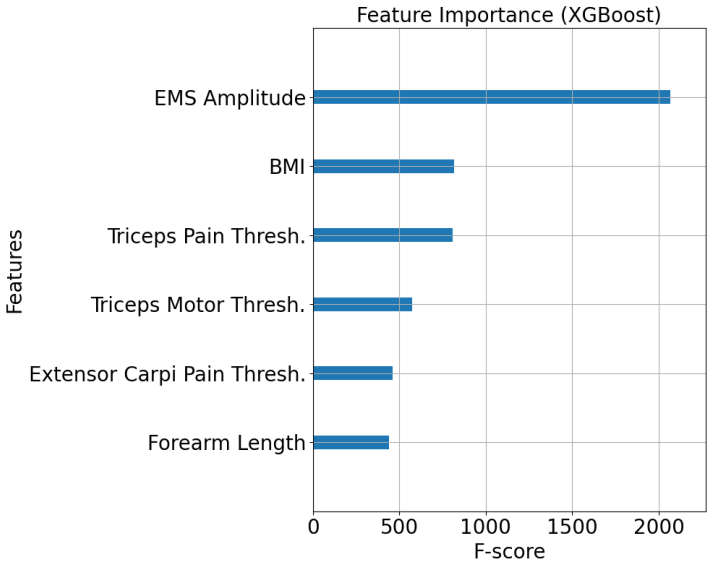


Figure 5.12: Feature importance scores from the XGBoost model, ranked by F-score. © 2025 IEEE. Reprinted, with permission, from Vrontos, Zolnouri, Nitsch, et al. (2025).

5.3.4 Discussion of Part B

The analysis presented in Part B demonstrated the feasibility of using a ML approach to personalize EMS-based haptic feedback. The primary finding was that the predictive models could predict the perceptual outcome of a given EMS amplitude with F1-scores of up to 77%, confirming the hypothesis (H1.4) that a predictive relationship exists between user-specific features and their subjective experience. While XGBoost showed the highest nominal performance (77%), the F1-scores for Random Forest (73%) and SVC (72%) were strictly comparable, suggesting that the underlying features provide a robust predictive signal regardless of the specific classifier used. This result is a significant step toward creating adaptive haptic systems that can move beyond a "one-size-fits-all" approach—overcoming the critical limitation of fixed-parameter systems identified in Section 2.3 (Yang et al., 2025), which the systematic synthesis (Section 3.3) revealed as the pervasive standard in current research. However, a notable limitation across all tested models was the difficulty in accurately classifying the "equal weight" perception (class 1). As illustrated in the confusion matrices, the models' recall for the 'Equal' class was lower than for the distinct 'Lighter' and 'Heavier' conditions. This reflects

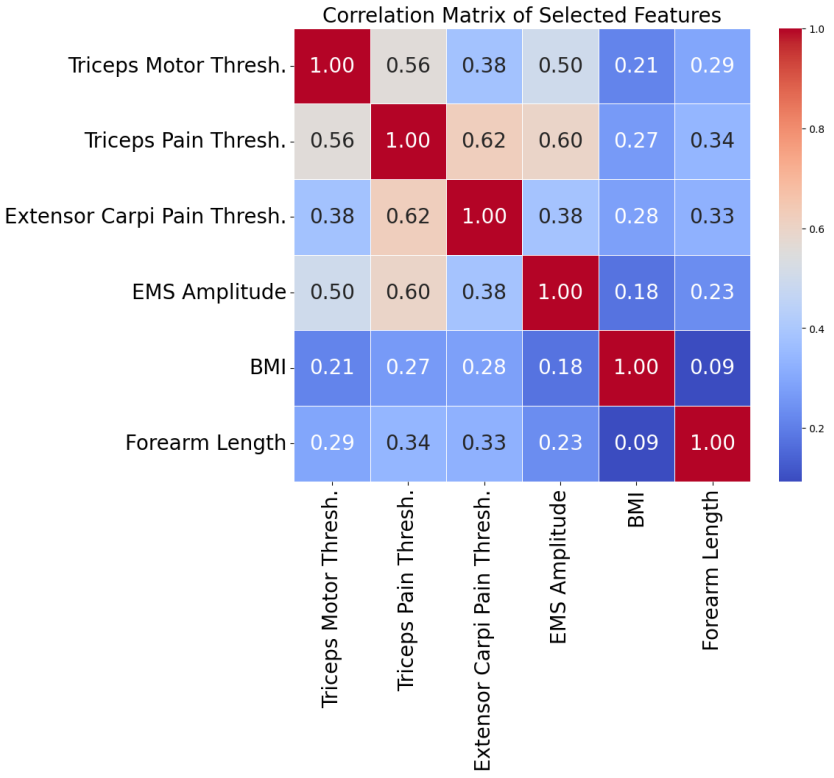


Figure 5.13: Correlation matrix for the six selected features. © 2025 IEEE. Reprinted, with permission, from Vrontos, Zolnouri, Nitsch, et al. (2025).

the psychophysical nature of the task: detecting equality involves operating at the very threshold of human perception—the Just Noticeable Difference (Lim et al., 2021). This creates a narrow perceptual window compared to the broader ranges of clear difference, resulting in a naturally imbalanced dataset. While the weighted evaluation metrics correctly adjust for this natural frequency, they do not distinguish between the specific costs of misclassification—such as failing to detect equality versus confusing weights. Future iterations could employ specific oversampling techniques or cost-sensitive learning to further sensitize the models to this narrower perceptual band—a necessary refinement to overcome the inherent subjective difficulty of the task and ensure the fine-grained control required for real-world applications.

The feature importance analysis provided crucial insights into the drivers of weight perception and strongly supported the second hypothesis (H1.5). As expected, the

applied EMS Amplitude was, by a substantial margin, the most influential predictor, confirming that the direct modulation of muscle contraction is the primary mechanism for altering perceived weight. Critically, the analysis also revealed that user-specific characteristics form a second tier of significant predictors, with BMI and the individually calibrated Triceps PT being the most important. The low correlation of features like BMI with other predictors indicates that they contribute unique, non-redundant information related to an individual's biomechanics and physiology. Physiologically, this aligns with the mechanism described in Section 2.4, where subcutaneous fat actively alters current diffusion—forcing flow through the dermis rather than acting purely as an insulator (Seno et al., 2019)—thereby making anthropometric data essential for accurate prediction. This finding provides quantitative evidence that truly personalized models must account for both the applied EMS and the unique physical and physiological characteristics of the user.

The effectiveness of the predictive models, even with a limited feature set, underscores the practicality of this data-driven approach for personalizing EMS. The observation that all tested classifiers yielded similar performance suggests that the personalization potential is rooted in the quality of the selected features rather than the specific model architecture. This feasibility lays the foundation for scalable, adaptive solutions in VR/AR and rehabilitation, where precise proprioceptive feedback can elevate user experience and therapeutic efficacy. While the current models serve as proofs-of-concept, their limitations define clear avenues for future work. The models' generalizability is constrained by the sample size and the specific 2 kg to 3 kg weight range used for data collection. Future research should aim to validate and expand these findings with larger, more diverse cohorts and a broader range of dynamic conditions to better reflect real-world scenarios.

5.4 Overall Interim Conclusion for Study 1

This first empirical study yielded a two-fold contribution that provides a robust foundation for rendering realistic weight sensations with EMS. The investigation began by addressing a fundamental gap in the literature regarding the most effective EMS strategy. The findings from Part A provide the first systematic, quantitative evidence that a synergistic, dual-muscle EMS strategy is fundamentally superior to a single-muscle EMS approach. This superiority was demonstrated not only in the magnitude of the perceived weight increase but also, critically, in its perceptual realism, establishing a new evidence-based baseline for effective EMS weight rendering that aligns with the body's natural biomechanics.

Building upon this foundational principle, the analysis in Part B demonstrated the feasibility of a data-driven, personalized approach to address the challenge of inter-subject variability. The development of predictive models, which achieved F1-scores of up to 77% in predicting perceptual outcomes, serves as a preliminary proof-of-concept. The feature importance analysis further provided a key insight: effective personalization models must integrate both the applied EMS parameters and the user's unique physiological and anthropometric characteristics, such as BMI and individual PTs.

Taken together, the findings from this study provide a clear path forward: they establish what to do (employ a dual-muscle strategy) and how to refine it (through data-driven personalization). While providing a robust foundation, this study's intentionally controlled design highlights the critical importance of the moderating factors that were held constant. The next chapter will build directly upon this work by systematically investigating the impact of ergonomics and a wider range of weight parameters, further advancing the development of a comprehensive framework for personalized EMS.

6 Empirical Study 2: Effects of Posture and Augmentation Parameters on Weight Perception[1]

6.1 Objective and Hypotheses

While the first empirical study established a superior dual-muscle EMS strategy (Part A) and demonstrated the feasibility of a data-driven personalization approach (Part B), the practical implementation of such models requires a crucial missing component: a quantitative understanding of the core psychophysical relationship. The ML models proved that personalization is necessary by linking user traits to perceived outcomes, but they did not systematically quantify the core relationship between a given EMS intensity and the resulting perceived weight. Furthermore, it is unknown how this fundamental mapping is affected by the context of the interaction.

Therefore, the primary objective of this second empirical study was to characterize the psychophysical relationship mapping EMS intensity to perceived weight increase for the established dual-muscle strategy. A secondary objective was to systematically characterize how this relationship, and the resulting perceived realism, is moderated by three key categories of variables:

1. A key ergonomic factor, specifically the user's posture as defined by the elbow

[1]This chapter is adapted from the author's previously published, peer-reviewed article: Vrontos, A., Nitsch, V., Mertens, A., & Brandl, C. (2026). Characterizing EMS-Induced Haptic Weight Perceptions: Effects of Posture, Augmentation Parameters, and User Variability. *IEEE Transactions on Haptics*. The author conceptualized and designed the experiment, performed the experimental work, carried out data cleaning and data analysis, and drafted the manuscript. Prof. Dr.-Ing. Verena Nitsch, Prof. Dr.-Ing. Alexander Mertens and Dr.-Ing. Christopher Brandl contributed through supervision, conceptual guidance, funding acquisition, and the review and editing of the final manuscript. Specifically, Sections 6.1, 6.2, and 6.4 have been adapted and paraphrased for the context of this thesis, while Section 6.3 is reprinted verbatim. The original work is licensed under a Creative Commons Attribution 4.0 International License.

angle.

2. Augmentation Parameters, including the magnitude of the weight increase and the base weight being augmented.

3. Individual User Characteristics, such as demographic, physical, and EMS Thresholds.

This investigation was guided by the following hypotheses, which translate the biomechanical constraints of the force-length relationship (Section 2.4.1), the psychophysical laws of intensity perception (Section 2.2.3), and the impact of physiological variability and sensorimotor memory identified in Sections 2.4.2 and 2.2.4—addressing the specific need for standardization and consistent parameterization called for in the systematic review (Section 3.4)—into specific empirical predictions:

H2.1: Ergonomics and Realism: The user's elbow angle will have a significant effect on perceived realism.

H2.2: Augmentation and Realism: The magnitude of the weight augmentation will influence realism, with the expectation that a perceptual optimum exists where the sensation is most realistic.

H2.3: Effectiveness: A larger physical weight difference between the reference and stimulated objects will require a proportionally higher EMS intensity to achieve the PSE.

H2.4: Individual user characteristics (such as age, BMI, and grip strength) will significantly influence the primary outcomes of perceived realism and the required EMS intensity.

H2.5: Learning Effect: A significant learning effect will occur, characterized by an increase in perceived realism ratings as users habituate to the EMS sensation over time.

6.2 Method

The methodology for this study builds upon the common framework detailed in the 'Overall Research Methodology' chapter (Chapter 4). This section describes the specific participants, design, apparatus, and procedures unique to this investigation.

6.2.1 Participants

A total of N = 35 healthy volunteers (23 male, 12 female) with a mean age of 26.2 years (SD = 4.4, range: 18-38) and a mean BMI of 24.35 (SD = 3.6, range: 19.6–36.9) were recruited for this study according to the standardized recruitment and screening protocols described in Section 4.2. The sample size was determined by an a priori power analysis, as detailed in the 'Overall Research Methodology' chapter (see Section 4.2), which was calculated to achieve a statistical power of 0.95. All participants provided written informed consent and were compensated for their time. The experimental posture adopted by participants is depicted in Figure 6.1.

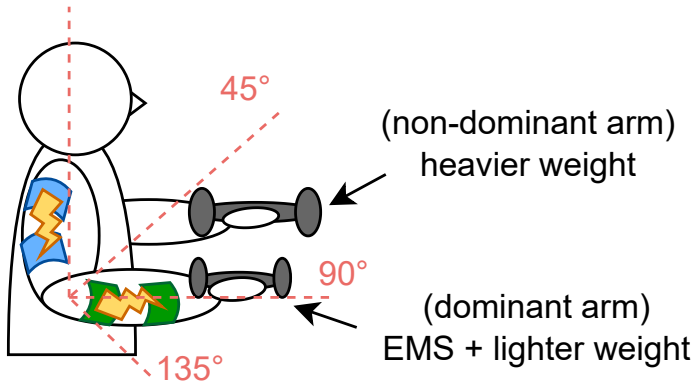


Figure 6.1: Illustration of the experimental procedure for Study 2. Participants compared a lighter weight in the dominant arm (with EMS) to a heavier reference weight in the non-dominant arm while holding one of three prescribed elbow angle postures (45°, 90°, or 135°). Reprinted from Vrontos et al. (2026).

6.2.2 Apparatus and Materials

The core EMS and control system (HASOMED© P24 device, axion electrodes, Lenovo ThinkPad with Python software) used in this study are detailed in Section 4.3. The specific materials unique to this experiment included a set of five physical weights used for the weight-matching task: a MQ3 controller (0.15 kg) and four dumbbells of 0.5 kg, 1 kg, 3 kg, and 5 kg. A goniometer was also used by the experimenter to establish the initial elbow angle and continuously monitor the limb for potential drift. Throughout the procedure, the participants' arms remained unsupported to ensure active muscular

engagement. This lack of external support was critical for generating the internal torque necessary to stabilize the limb against the EMS, a biomechanical requirement for eliciting the sense of effort that underpins the weight illusion.

6.2.3 Experimental Design

The study employed a within-subjects design with two primary independent variables:

- Elbow Angle: Manipulated at three levels to represent different postures: 45° (acute), 90° (perpendicular), and 135° (obtuse).
- Weight Combination: Ten unique pairs of a lighter weight and a heavier reference weight, created from the pool of five available weights.

This design resulted in a total of 30 trials per participant (3 angles × 10 weight pairs). The presentation order of the three elbow angle blocks, as well as the order of the 10 weight combinations within each block, was randomized for each participant to mitigate ordering effects.

The primary dependent variables measured in each trial were:

- Absolute EMS Intensity at PSE: The raw EMS amplitude (in mA) required to reach the PSE, recorded separately for the upper and lower arm.
- Normalized EMS Intensity at PSE: The EMS amplitude required to reach the PSE, calculated as a percentage of the individual's calibrated [MT, PT] range.
- Perceived Realism: A subjective rating on a 7-point Likert scale assessing the naturalness of the weight sensation.

6.2.4 Procedure

The experimental session followed the standardized protocols for participant preparation, covariate measurement, and individual EMS calibration, as detailed in the Data Collection Procedures section of the 'Overall Research Methodology' chapter (see Section 4.4). The main experimental task unique to this study was a weight-matching procedure. In each of the 30 trials, participants were seated and held the lighter weight in their dominant (stimulated) arm and the heavier reference weight in their non-dominant arm, while maintaining one of the three prescribed elbow postures.

To determine the PSE, the EMS amplitude was programmatically increased in a 30-second linear ramp. Starting at their respective MTs, the amplitude for both the triceps and forearm incremented proportionally every second to reach their PTs simultaneously. Each 1-second step was rounded to the nearest 0.5 mA to match the hardware's resolution. Participants were instructed to say "stop" at the precise moment the perceived weight in their stimulated arm felt equal to the reference weight. The EMS amplitude at this point was recorded. Immediately following this, participants rated the realism of the weight augmentation on a 7-point Likert scale (see Appendix D.2).

6.3 Results[2]

The findings from the second empirical study are presented in this section.

6.3.1 Effect of Experimental Conditions on Perceived Realism

Effect of Elbow Angle

A one-way repeated measures ANOVA revealed a significant main effect of elbow angle on perceived realism ($F(2, 68) = 4.69$, $p = 0.012$, $\eta_p^2 = 0.12$). As shown in Figure 6.2, the realism ratings varied across the three postures. Post-hoc pairwise comparisons with Bonferroni correction were conducted to identify specific differences. The results showed that the 90° condition ($M = 4.59$, $SD = 0.93$) was rated as significantly more realistic than the 45° condition ($M = 4.27$, $SD = 0.96$), $t(34) = -2.88$, $p = 0.02$, $d = 0.34$. No other pairwise comparisons were statistically significant ($p > 0.05$). This indicates that perpendicular (90°) and more open (135°) elbow angles are preferable for preserving the realism of the sensation, whereas the believability is significantly degraded when the elbow is in a more acute (45°) angle.

[2]This section is reprinted verbatim from: Vrontos, A., Nitsch, V., Mertens, A., & Brandl, C. (2026). Characterizing EMS-Induced Haptic Weight Perceptions: Effects of Posture, Augmentation Parameters, and User Variability. *IEEE Transactions on Haptics*. Open Access. This article is licensed under a Creative Commons Attribution 4.0 International License.

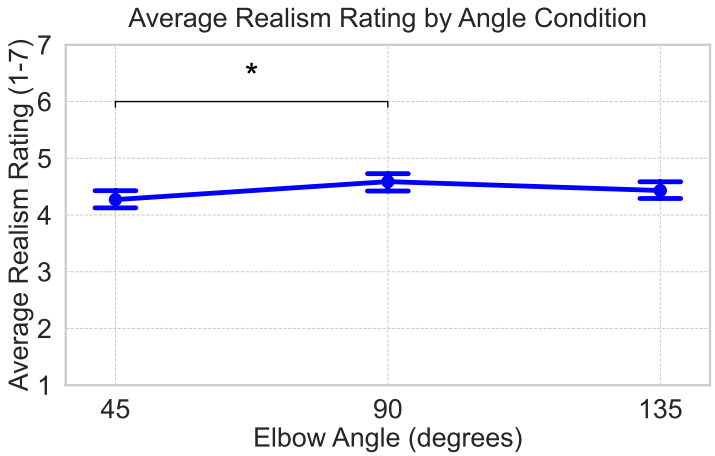


Figure 6.2: Average realism rating as a function of the elbow angle. The 90° condition was rated as significantly more realistic than the 45° condition. The asterisk (*) denotes this statistically significant difference ($p < 0.05$). Error bars represent the 95% confidence interval. Reprinted from Vrontos et al. (2026).

Analysis of Learning Effect

A repeated measures ANOVA showed a significant effect of the chronological block number on realism ($F(2, 68) = 7.13$, $p = 0.002$, $\eta_p^2 = 0.17$). Post-hoc tests revealed that realism ratings were significantly higher in Block 2 ($p = 0.001$) and Block 3 ($p = 0.032$) compared to Block 1. There was no significant difference between Block 2 and Block 3 ($p > 0.05$). This indicates a statistically significant learning or habituation effect after the initial block of trials, as shown in Figure 6.3. Crucially, a follow-up Linear Mixed Model analysis (required due to the randomized block design) revealed no significant interaction between the chronological block and the elbow angle (all $p > .41$). This confirms that the learning effect was uniform across conditions and, due to the randomized block order, did not bias the main effects of posture.

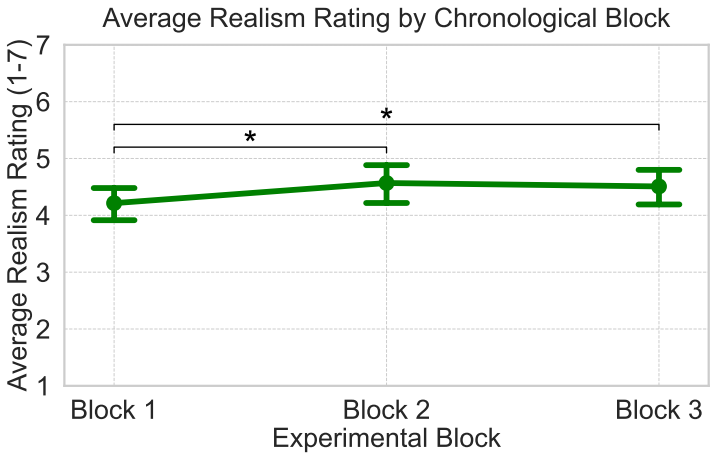


Figure 6.3: Illustration of the learning effect on perceived realism across the three chronological blocks of the experiment. The asterisks (*) denote a significant increase in realism from Block 1 to both Block 2 and Block 3 ($p < 0.05$). Error bars represent the 95% confidence interval. Reprinted from Vrontos et al. (2026).

6.3.2 Effect of Weights on Perceived Realism

Effect of Weight Combination

A repeated measures ANOVA revealed a highly significant main effect of the specific weight pair on perceived realism ($F(9, 306) = 8.82$, $p_{\text{GG-corr}} < .001$, $\eta_p^2 = 0.21$). Mauchly's test indicated that the assumption of sphericity was violated ($p < .05$); therefore, degrees of freedom were corrected using Greenhouse-Geisser estimates ($\epsilon = 0.29$). Post-hoc pairwise comparisons with Bonferroni correction were performed to identify specific differences between the 10 combinations. The results indicated a clear ranking of the combinations, as summarized in Figure 6.4. The pair rated as significantly more realistic was '3 vs 5 kg', while '0.15 vs 5 kg' was rated significantly lower than most other combinations. In general, pairs with heavier base weights and moderate ratios performed best, while those with the lightest base weight (0.15 kg) or extreme ratios consistently received the lowest ratings. The post-hoc tests confirmed that the '3 vs 5 kg' pair was rated as significantly more realistic than numerous other combinations, including '0.15 vs 1 kg'

($p < .001$, $d = 1.35$), as well as '0.5 vs 1 kg' ($p = .002$, $d = 0.76$) and '1 vs 5 kg' ($p = .002$, $d = 0.82$).

This finding is further supported by an analysis of rating frequencies. The '3 vs 5 kg' combination elicited the highest proportion of "high" realism ratings (scores ≥ 5) at 82.9%, while conversely having the lowest proportion of "low" realism ratings (scores ≤ 3) at only 5.7%. In contrast, combinations like '0.15 vs 5 kg' had a much lower percentage of high realism ratings (40.0%). These results clearly identify the '3 vs 5 kg' pairing as the most effective combination for producing a consistently realistic weight sensation.

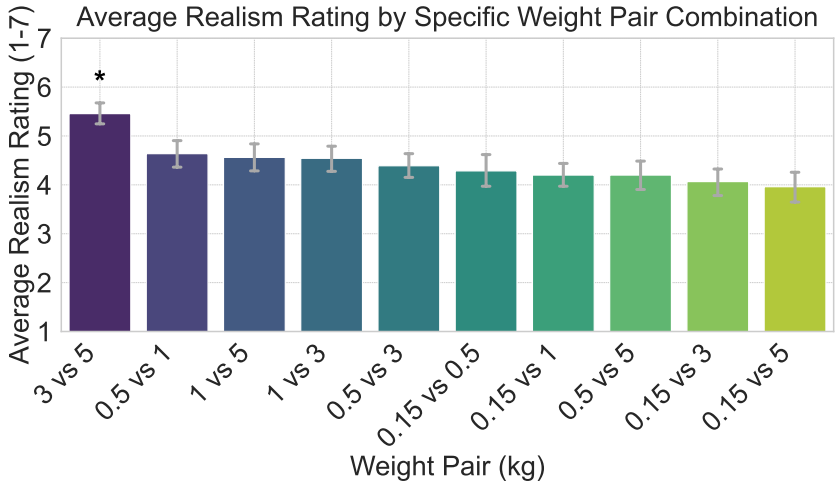


Figure 6.4: Average realism rating for each of the 10 weight pair combinations, sorted from most to least realistic. The asterisk (*) marks the '3 vs 5 kg' pair, which was rated as significantly more realistic than numerous other combinations. Error bars represent the 95% confidence interval. Reprinted from Vrontos et al. (2026).

Effect of Weight Difference

To investigate if the difference between the compared weights influenced perceived realism, a one-way repeated measures ANOVA was conducted. The analysis revealed a highly significant main effect of the weight difference on realism ratings ($F(8, 272) = 5.07$, p-GG-corr $= .006$, $\eta_p^2 = 0.13$).

As the assumption of sphericity was violated, reported p-values reflect the Greenhouse-Geisser correction.

As illustrated in Figure 6.5, the relationship was non-linear. Post-hoc pairwise comparisons with Bonferroni correction showed that a weight difference of 2.0 kg was a perceptual "sweet spot", being rated as significantly more realistic than several other differences, including 0.85 kg ($p < .001$, $d = 0.88$), 2.85 kg ($p < .001$, $d = 0.95$), and 4.85 kg ($p < .001$, $d = 0.85$). To formally test the shape of this relationship, we fitted a quadratic mixed model ($Realism \sim \Delta W + \Delta W^2$) and compared it to a linear baseline. The quadratic model provided a significantly better fit (AIC: 3418 vs. 3436), with a significant negative squared term ($\beta = -0.08, p < .001$), statistically confirming the inverted-U profile of the sensation.

A follow-up analysis was performed to determine if the consistency of realism ratings (i.e., the standard deviation) was related to the weight parameters. Linear regression analyses found no significant relationship between the standard deviation of realism ratings and the weight difference ($R^2 = 0.07$, $p = .461$), the average weight of the pair ($R^2 = 0.07$, $p = .455$), or the highest weight in the pair ($R^2 < .01$, $p = .880$). This suggests that while the average realism rating is sensitive to the weight difference, the consistency of those ratings is not systematically affected by the magnitude of the weights.

Comparison of Weight Parameters

To determine which physical parameter best predicts perceived realism, we conducted a formal model comparison between three potential predictors: Absolute Weight Difference, Weight Ratio (Weber's Law), and Physical Base Weight. The analysis identified Physical Base Weight as the strongest single predictor (AIC = 3334). While the model based on Weight Ratio also performed well (AIC = 3346), it was statistically inferior to the Base Weight model. Both models significantly outperformed the original Weight Difference model (AIC = 3436), suggesting that the starting weight magnitude plays a statistically stronger role than the difference itself.

6.3.3 Interaction of Angle and Weight Combination

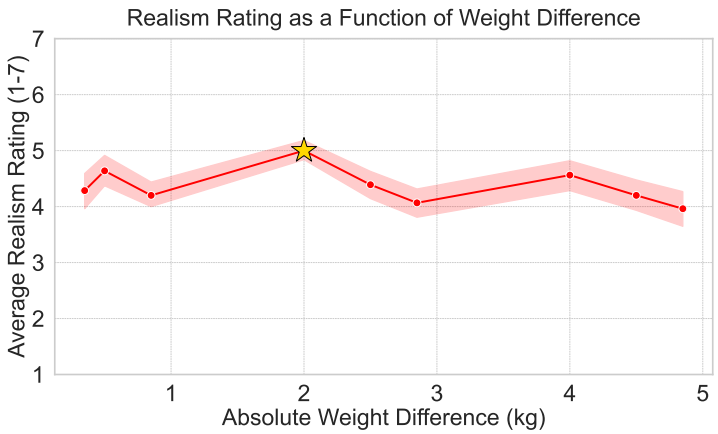


Figure 6.5: The non-linear relationship between the absolute difference in weight and the perceived realism of the sensation. The gold star highlights the perceptual optimum at a 2.0 kg difference, which was rated as significantly more realistic than several other differences. The shaded area represents the 95% confidence interval. Reprinted from Vrontos et al. (2026).

To test for an interaction effect between elbow angle and weight combination on perceived realism, we analyzed the interaction term using a Two-Way Repeated Measures ANOVA. The analysis revealed that the interaction effect was not statistically significant ($F(18, 612) = 0.86, p = .497, \eta_p^2 = .02$). This indicates that the effect of the weight combination on realism did not significantly differ across the three elbow angles tested (45°, 90°, and 135°). As illustrated in Figure 6.6, the pattern of how different weight pairs were rated remained largely consistent across each angle; for example, the '3 vs 5 kg' combination consistently received the highest realism ratings regardless of the elbow posture. The absence of a strong interaction suggests that the perceptual effects of weight and angle are largely additive rather than interdependent. Crucially, this non-significant result validates the independent analysis and reporting of the main effects in the preceding sections.

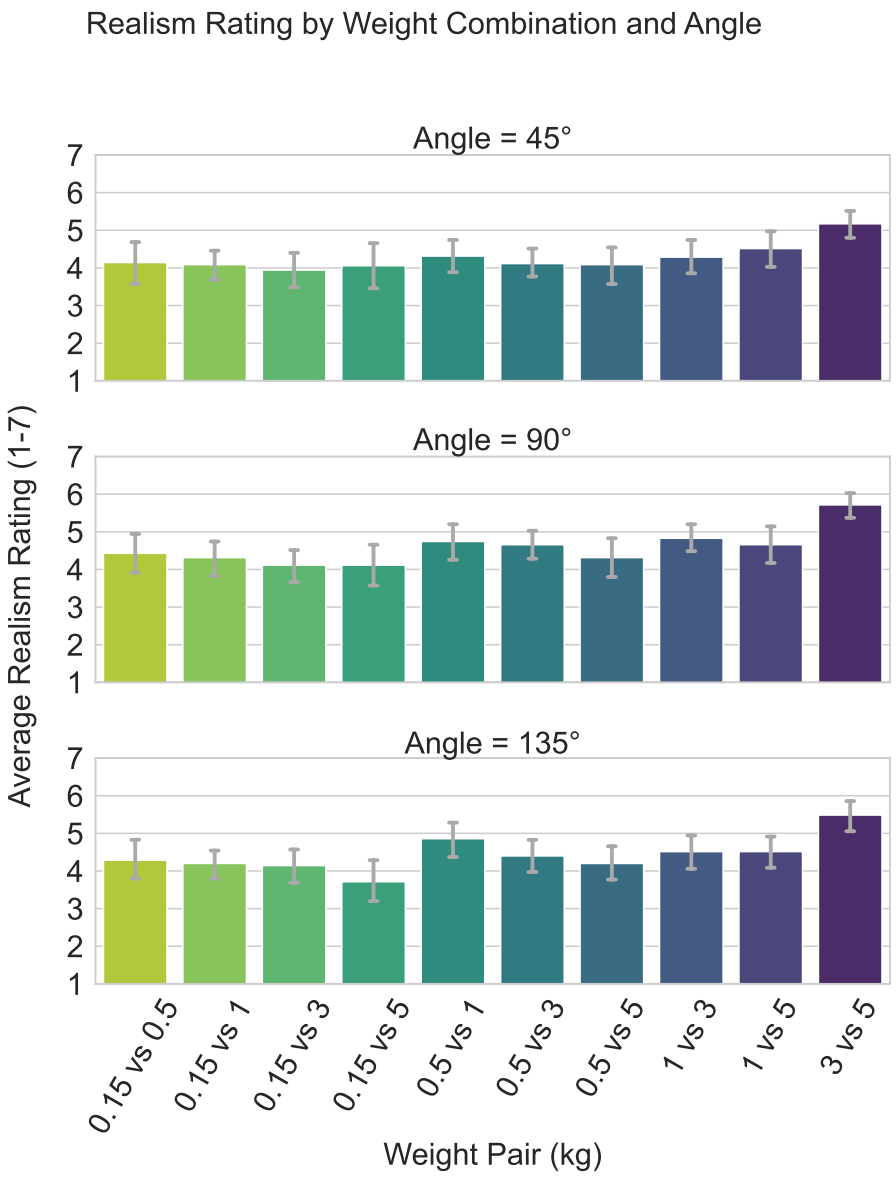


Figure 6.6: Average realism rating for each weight pair, grouped by elbow angle. The similar pattern of ratings across all three angles visually supports the statistical finding of no significant interaction effect. Error bars represent the 95% confidence interval. Reprinted from Vrontos et al. (2026).

6.3.4 Relationship Between EMS Intensity and Weight Sensation

To understand how the experimental conditions affected the PSE, we analyzed the PSE in two ways. First, we examined the absolute EMS intensity at PSE (mA) to understand the raw current required. Second, we analyzed the normalized EMS intensity at PSE—calculated as a percentage of each user's individual dynamic range [MT, PT]—to account for inter-subject variability and provide a more comparable measure of perceived weight sensation.

Absolute EMS Intensity at PSE (mA)

The relationship between the experimental conditions and the absolute EMS intensity is illustrated in Figure 6.7. The top and bottom-left panels show a clear and near-linear positive relationship between the absolute weight difference and the PSE for each elbow angle. To quantify this trend, the required EMS intensity for the upper arm started at approximately 28 mA for the smallest weight differences and increased to around 43 mA for the largest, while the lower arm followed a similar path from roughly 22 mA to 31 mA. In all conditions, upper arm consistently required a substantially higher EMS intensity than lower arm; this is attributable in part to the larger electrode surface area used for the triceps (50 cm^2 vs. 25 cm^2), which necessitates higher absolute current to maintain effective current density. Furthermore, the required EMS intensity was lower in the 135° posture. The bottom-right panel summarizes this main effect of posture ($F(2, 68) = 4.87, p = .011, \eta_p^2 = 0.13$). To verify the nature of this relationship, we performed a Repeated Measures ANOVA ($Intensity \sim Angle \times \Delta Weight$), which revealed no significant interaction ($F(16, 544) = 0.77, p = .724, \eta_p^2 = 0.02$). This confirms that the effects are additive: the weight difference drives the slope of the current increase, while the elbow angle acts as a constant biomechanical offset.

Of the ten weight combinations tested, a weight difference of 2.0 kg was uniquely represented by two distinct pairs ('1 vs 3 kg' and '3 vs 5 kg'). This provided a direct opportunity to investigate whether the required EMS intensity is affected by the absolute magnitude of the weights, independent of their difference. However, as shown in Figure 6.8, the analysis revealed no substantial difference in the absolute EMS intensity required for the lighter

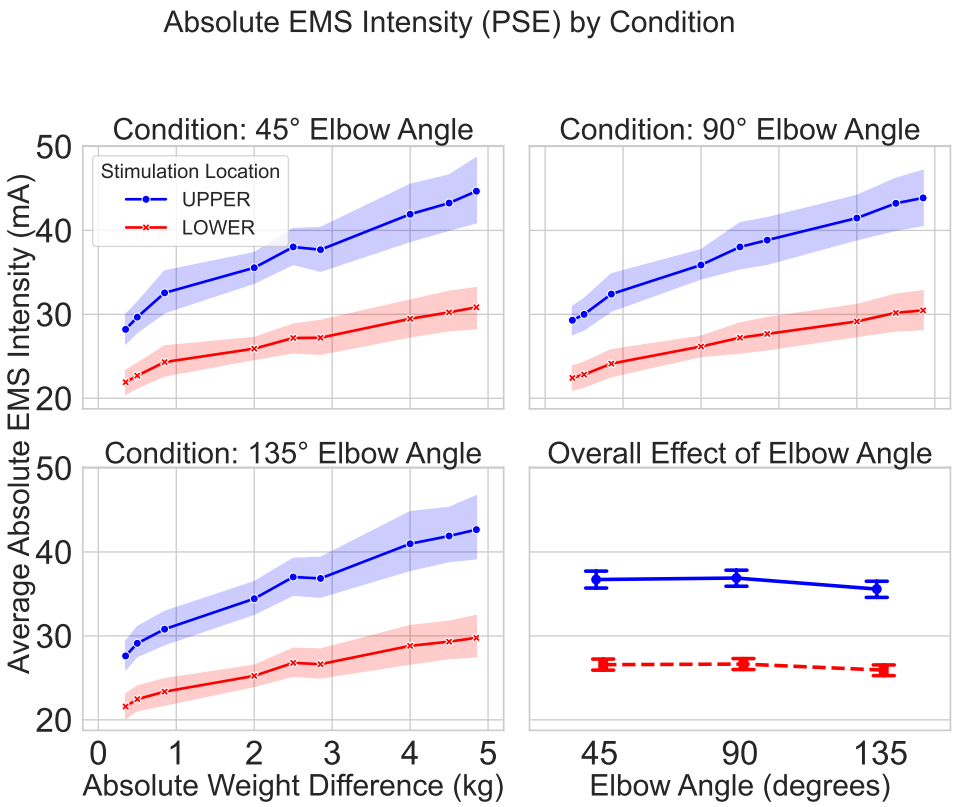


Figure 6.7: Absolute EMS intensity required to reach the PSE. The three main panels show that for each elbow angle, the required EMS intensity increases with greater weight differences and is consistently higher for the upper arm. The bottom-right panel summarizes the overall effect of angle, showing the average EMS intensity for each condition. Reprinted from Vrontos et al. (2026).

'1 vs 3 kg' pair versus the heavier '3 vs 5 kg' pair ($t(34) = 0.57, p = .570, d = 0.06$). This was true for both upper and lower arm. This finding suggests that, for a given weight difference, the absolute magnitude of the weights does not significantly impact the required current.

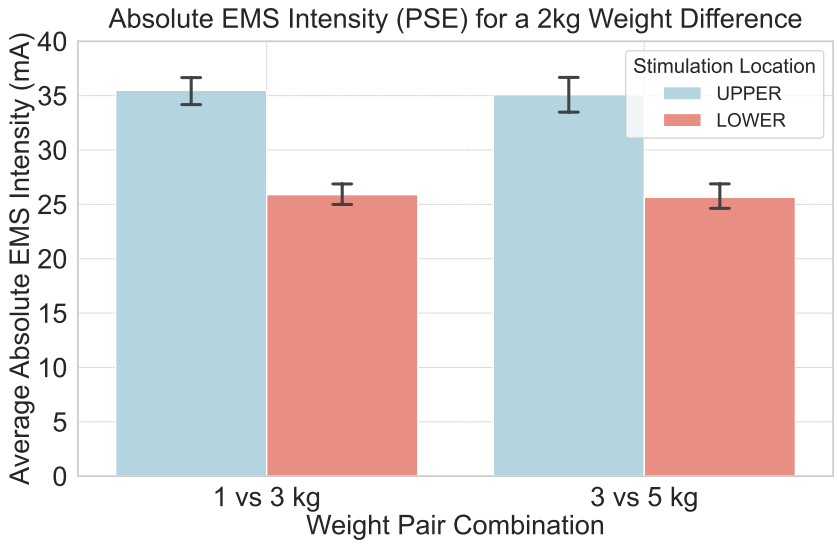


Figure 6.8: Comparison of the absolute EMS intensity at PSE for the two weight combinations with a 2 kg difference. Error bars represent the 95% confidence interval. Reprinted from Vrontos et al. (2026).

Normalized EMS Intensity at PSE (%)

After normalizing the EMS intensity required at PSE to account for individual EMS thresholds (as defined in Section 4.4.2), the relationship between the experimental conditions and EMS intensity was re-examined, as illustrated in Figure 6.9. The near-perfect overlap of the two response curves is a direct consequence of the experimental design; the EMS intensity for both muscles was increased together in a 1:1 ratio of their respective dynamic ranges.

The positive and near-linear relationship between weight difference and normalized EMS intensity remained strong and consistent across all angles. Specifically, the required normalized EMS intensity began at approximately 30% of the users' dynamic range for the smallest weight difference (0.35 kg)

and increased steadily to about 70–75% for the largest augmentations of nearly 5 kg. Furthermore, the effect of elbow posture on the required EMS intensity was preserved, with 135° requiring on average a bit less consistently ($F(2, 68) = 3.61, p = .032, \eta_p^2 = 0.10$). This is a key finding because it confirms that the influence of elbow angle on the perceived weight augmentation is a genuine postural effect, as the pattern persisted even after normalizing for each user's individual sensitivity to the EMS.

As with the absolute data, a follow-up analysis of the normalized EMS intensity at PSE confirmed there was no substantial difference between the lighter '1 vs 3 kg' pair and the heavier '3 vs 5 kg' pair, as seen in Figure 6.10 ($t(34) = 1.28, p = .209, d = 0.14$). This reinforces that the perceived effort is dependent on the relative weight difference, not the absolute magnitude of the weights.

6.3.5 Correlation of Outcome Measures with Participant Characteristics

This section analyzes the relationship between the primary outcome measures and the participants' individual characteristics. The findings are grouped by the type of characteristic, with the full correlation matrices presented in Table 6.1 and Table 6.2.

Correlations with Demographic and Physical Characteristics

First, we examined the relationship between the primary experimental outcomes (EMS intensity at PSE and realism) and the participants' demographic and physical characteristics, as shown in Table 6.1. The analysis revealed two notable findings. For perceived realism, both age ($r = .53, p = .001$) and BMI ($r = .48, p = .003$) were strong, significant positive correlates. Additionally, the normalized EMS intensity at PSE showed a significant negative correlation with maximum grip force ($r \approx -.52, p = .002$), suggesting that stronger participants required a relatively lower percentage of their individual dynamic range ([MT, PT] range) to perceive a given weight.

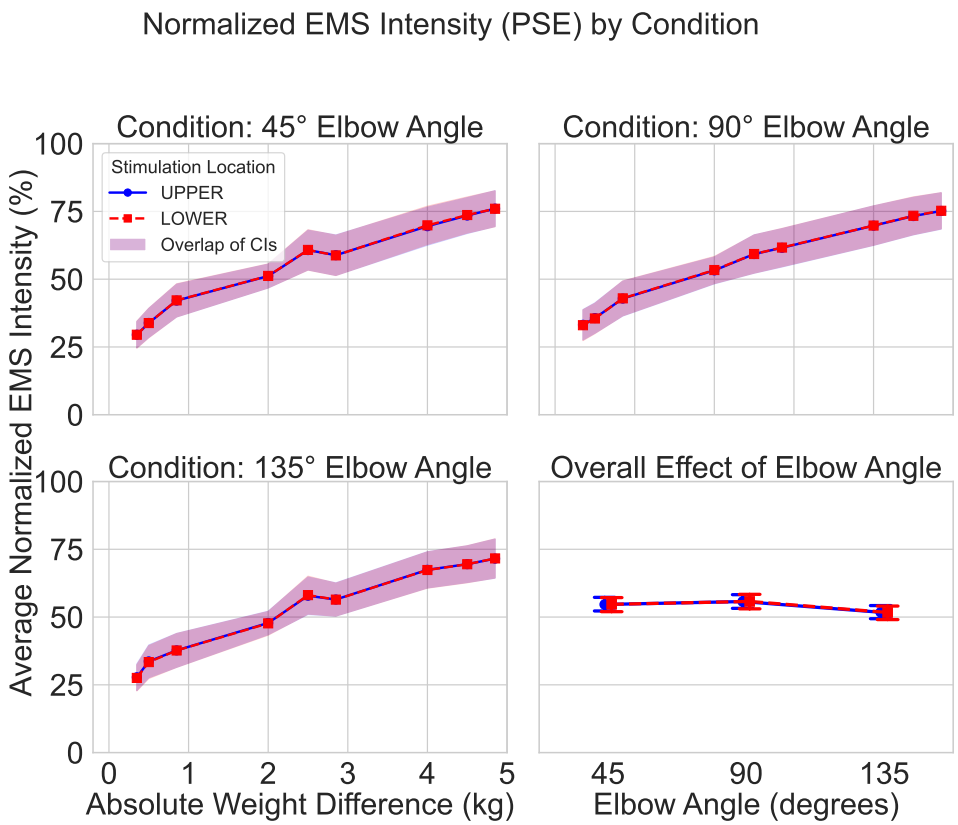


Figure 6.9: Normalized EMS intensity required to reach the PSE. The three main panels show that the required normalized EMS intensity increases with greater weight differences, with the perfect overlap of the upper and lower arm data being an expected consequence of the 1:1 EMS ratio. The bottom-right panel summarizes the overall effect of angle, confirming that the effect of angle on required EMS intensity persists even after normalization. Reprinted from Vrontos et al. (2026).

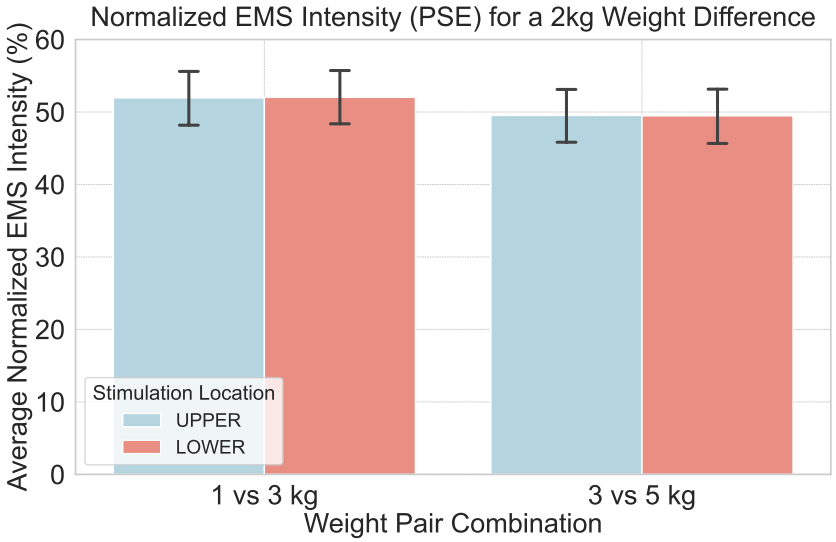


Figure 6.10: Comparison of the normalized EMS intensity at PSE for both the '1 vs 3 kg' and '3 vs 5 kg' pairs. Error bars represent the 95% confidence interval. Reprinted from Vrontos et al. (2026).

Table 6.1: Pearson Correlations (r) of Experimental Outcomes with Demographic and Physical Characteristics. Reprinted from Vrontos et al. (2026).

Outcome Measure	**Age**	**Gender (F)**	**Height**	**Weight**	**BMI**	**Grip Force**	**Upper Arm Circ.**
EMS Intensity (PSE)							
Absolute - Upper (mA)	.10	-.05	.19	.31	.28	.21	.29
Absolute - Lower (mA)	.31	-.27	.33	.38*	.26	.36*	.39*
Normalized Up./Low. (%)	-.30	.28	-.34*	-.32	-.22	-.52**	-.33
Realism							
Average Realism Score	.53***	-.09	-.14	.28	.48**	.09	.32

Note: Table displays Pearson's r-values. F = Female; Circ. = Circumference; Abs. = Absolute; Norm. = Normalized; Up. = Upper; Low. = Lower.
*$p < .05$, **$p < .01$, ***$p < .001$.

Correlations with Individual EMS Thresholds

Next, we analyzed how the participants' individual EMS thresholds correlated with the main experimental outcomes (Table 6.2). The absolute EMS intensity at PSE was almost entirely determined by the participant's lower and upper arm pain thresholds. The correlation between the absolute EMS intensity at PSE on the upper arm and the upper arm pain threshold was exceptionally strong ($r = .82, p < .001$), as was the case for the lower arm ($r = .87, p < .001$). This confirms that a participant's individual EMS thresholds are the primary factor dictating the absolute EMS intensity at PSE required for the weight sensation. Interestingly, all individual EMS thresholds showed significant negative correlations with the normalized EMS intensity at PSE, reinforcing that a participant's individual EMS thresholds are a key factor in their overall experience.

Table 6.2: Pearson Correlations (r) of Experimental Outcomes with Individual EMS Thresholds. Reprinted from Vrontos et al. (2026).

	Upper Arm Thresholds			**Lower Arm Thresholds**		
Outcome Measure	**Sensory**	**Motor**	**Pain**	**Sensory**	**Motor**	**Pain**
EMS Intensity (PSE)						
Absolute - Upper (mA)	.28	.36*	.82***	.31	.41*	.70***
Absolute - Lower (mA)	.39*	.44**	.59***	.53***	.66***	.87***
Normalized Up./Low. (%)	-.47**	-.49**	-.45**	-.34*	-.43**	-.35*
Realism						
Average Realism Score	.05	.30	.21	-.06	.20	.29

Note: Table displays Pearson's r-values. Abs. = Absolute; Norm. = Normalized; Up. = Upper; Low. = Lower.
*$p < .05$, **$p < .01$, ***$p < .001$.

6.3.6 EMS Efficiency

To identify which participants received the most effective simulation, or the best "bang for the buck", we calculated an "EMS efficiency" score. This metric was defined as the ratio of the average perceived realism score to

the average normalized EMS intensity required at the PSE, calculated separately for the upper and lower arm. A higher score indicates that a participant achieved a greater sense of realism for a given amount of relative EMS intensity.

We then analyzed the correlation between this efficiency score and participant demographic and physical characteristics. The results for both upper and lower arm were identical due to the 1:1 EMS ratio. Table 6.3 presents all significant correlations with a coefficient greater than 0.3. The strongest relationships included age, grip force, upper arm circumference and motor thresholds. These findings suggest a clear profile of the most EMS-efficient user: an individual who is older, possesses greater physical strength and a larger build (as indicated by upper arm circumference, weight and BMI), and is also less sensitive to EMS (indicated by higher motor and pain thresholds) tends to achieve the most realistic sensation for the least normalized EMS intensity. To statistically validate the stability of this metric, we performed a split-half reliability analysis (odd vs. even trials), which yielded an exceptionally high Spearman-Brown coefficient of $r_{sb} = 0.97$, confirming that efficiency is a stable user trait. Furthermore, a multiple linear regression analysis confirmed that these biological characteristics (Age, BMI, Grip Force) significantly predict a user's efficiency score ($F(3, 31) = 5.61, p = .003, R^2 = 0.35$), supporting its utility as a predictable design parameter.

6.4 Discussion

This study systematically investigated the factors that moderate the perception of EMS-based weight sensations, providing the first evidence-based guidelines for haptic design by characterizing the quantitative function mapping a target weight increase (in kg) to the required EMS intensity (in mA), demonstrating that posture is a critical factor for perceived realism, and establishing the significant correlation between individual user characteristics and these perceptual outcomes. The findings confirm that the perceived realism and effectiveness of EMS are not arbitrary, but are systematically influenced by user posture, the parameters of the weight augmentation, and individual user characteristics—providing the necessary empirical evidence to transition away from the static, open-loop strategies that the systematic literature review (Section 3.3) identified as the prevailing but limited standard in the field.

The results provide the first quantitative evidence that ergonomics are critical for the

Table 6.3: Pearson Correlations (r) of EMS Efficiency with Demographic, Physical, and EMS Threshold Characteristics. Reprinted from Vrontos et al. (2026).

Demographic & Physical Characteristics					
Efficiency Score	**Age**	**Grip Force**	**Upper Arm Circ.**	**Weight**	**BMI**
Upper/Lower Arm	.47**	.46**	.43**	.40**	.40**
Individual EMS Thresholds					
Efficiency Score	**UA Motor Th.**	**LA Motor Th.**	**LA Pain Th.**	**UA Pain Th.**	**UA Sensory Th.**
Upper/Lower Arm	.51**	.40**	.37*	.36*	.35*

Note: Table displays Pearson's r-values. Circ. = Circumference; UA/LA = Upper/Lower Arm; Th. = Threshold. *p < .05, **p < .01.

perceived realism of EMS haptics, confirming H2.1. The finding that a perpendicular 90° elbow angle was perceived as significantly more realistic than an acute 45° angle can be attributed to biomechanical familiarity; neutral holding postures are common for object manipulation and likely allow the artificial EMS contractions to integrate more seamlessly with existing proprioceptive signals, whereas acute angles may introduce conflicting joint tension. Furthermore, in line with H2.2, the discovery of a perceptual optimum, where a 2 kg weight augmentation was rated as most realistic, highlights the importance of sensory congruence. This suggests that while EMS can create powerful sensations, its realism is highest when the augmentation does not drastically conflict with the user's baseline perception of the object's weight. However, the analysis of the base weight supports a "Sensory Masking Hypothesis": a sufficient physical base weight is required to mask the cutaneous artifacts of EMS (Drewing & Lezkan, 2021; Li & Seifi, 2025). Trials with light base weights (0.15 kg) failed to mask these artifacts, resulting in poor perceived realism. This aligns with the theoretical risk described in Section 2.1, where ambiguous or poorly rendered sensations break immersion by drawing the user's attention to the interface rather than the interaction (Gao & Spence, 2025). Finally, the significant learning effect (H2.5), where perceived realism improved after the first block of trials, has direct practical implications, suggesting that user onboarding for EMS systems should include a brief habituation phase. Crucially, the stability of ratings over

time rules out physiological fatigue as a confounding factor.

A key finding of this study, supporting H2.3, is the near-linear positive relationship between the physical weight difference and the required normalized EMS intensity. This is particularly noteworthy as it contrasts with Stevens' Power Law, which suggests a non-linear, expansive relationship for the perception of heaviness (exponent ≈ 1.7) (J. Kim et al., 2022; Stevens, 1957, 1970). Instead, this finding aligns more closely with the literature that has demonstrated a linear link between muscular effort (measured via EMG) and perceived heaviness (Mangalam, Conners, & Singh, 2019). This suggests that the EMS-induced sensation in this context may be processed by the brain in a manner more akin to a direct sense of effort rather than a non-linear perceptual experience. In terms of biomechanics, the finding that the 135° posture required significantly less EMS intensity is driven by two factors: externally, the reduced gravitational moment arm lowers the torque required to support the limb; internally, the flexors benefit from passive elastic tension at open angles, whereas acute angles suffer from active insufficiency, necessitating higher voluntary drive (Leedham & Dowling, 1995; Memberg et al., 2003; X. Wang et al., 2017). Further supporting this, the analysis revealed that the required EMS intensity was driven by the relative weight difference, not the absolute magnitude of the weights; the fact that the 1 vs 3 kg and 3 vs 5 kg pairs required no significant difference in EMS intensity suggests that the brain calibrates the required effort based on the perceptual "gap" it needs to close to match the reference weight.

Perhaps the most significant contribution of this study is the quantitative demonstration that a "one-size-fits-all" approach to EMS is insufficient, confirming the theoretical limitations of fixed-parameter systems identified in Section 2.3. The correlation analysis revealed clear patterns linking individual user characteristics to haptic perception, providing strong support for H2.4. Regarding anthropometrics, higher BMI was a strong predictor of higher perceived realism. Physiologically, this is likely because subcutaneous fat alters the current path; as detailed in Section 2.4, higher fat content forces current to flow preferentially through the dermis and epidermis rather than penetrating directly to the muscle (Seno et al., 2019), potentially altering the sensation's quality. Distinctly, older age also correlated with higher perceived realism, though likely for different reasons. Physiologically, this may result from the age-related declines in proprioceptive acuity noted in Section 2.4, which could dampen the perception of unnatural EMS artifacts. Psychologically, it may reflect lower expectations or "haptic literacy" (Section 2.5): while expert users often view haptic artifacts critically as "noise" (C.-G. Lee et al., 2015; Söderström et al., 2022), novices may be less critical of the simulation (Lorenz et al., 2023; Zhou et al., 2007). Critically, the distinction between absolute and normalized EMS intensity provides a path toward personalization: while a user's abso-

lute tolerance for current is primarily a function of their PT, their "EMS efficiency"—the perceived realism achieved for a given normalized intensity—is linked to physical traits like strength. This aligns with findings that individuals with long-term physical training possess superior force sense acuity (Niespodziński et al., 2018; Proske & Gandevia, 2012) and distinct neural control strategies (Section 2.4), making them more responsive to the artificial cues. These findings provide a data-driven foundation for developing the adaptive, personalized models that the field requires.

In conclusion, this study provides a clear framework of the ergonomic and personal factors that govern EMS perception. However, several limitations must be acknowledged. First, the investigation was conducted using a quasi-static weight-matching task without congruent visual feedback, which is a critical component of most VR/AR applications (Berger et al., 2018; Hettiarachchi & Wigdor, 2016). While necessary for experimental control, this design implies that the findings may not fully translate to dynamic, continuous interactions typical of real-world object manipulation. Furthermore, to manage fatigue, each condition was tested only once per participant, preventing an assessment of intra-subject rating consistency. Methodologically, the use of a fixed 1:1 intensity ratio is a simplification adopted to isolate postural effects, though this linear coupling serves as a foundational step in exploring multi-channel proprioceptive feedback (Galofaro et al., 2022). However, computational models suggest that optimal agonist-antagonist ratios vary dynamically with posture (Gastaldi et al., 2020; McFarland et al., 2022), pointing to the need for real-time, posture-dependent scaling functions (Diaz et al., 2024). Regarding user variability, while Age and BMI were identified as predictors, the participant pool was limited to healthy adults aged 18–38; thus, generalizing these efficiency profiles to older or less fit populations requires caution. Similarly, the potential influence of 'haptic literacy' discussed earlier remains a theoretical interpretation, as prior gaming experience was not explicitly quantified. The limitations of this study—specifically the need to understand how these haptic principles integrate with other sensory modalities in a dynamic, closed-loop system—directly motivate the third and final empirical study of this thesis, which systematically investigates the principles of visuohaptic congruence.

6.5 Interim Conclusion

This second empirical study moved beyond foundational principles to characterize the key factors that govern the perception of EMS-based haptics. The findings indicate that ergonomics are critical, with neutral holding postures yielding significantly more realistic sensations due to superior biomechanical stability. Additionally, the discovery

of a "Sensory Masking" effect—where a sufficient physical base weight is required to hide stimulation artifacts—alongside the identification of a perceptual optimum, underscores the importance of sensory congruence in haptic design. Furthermore, the observation of a significant learning effect indicates that perception evolves rapidly, suggesting that a brief habituation phase may benefit the user experience.

A further contribution lies in the study's quantitative analysis. It characterizes the near-linear function mapping a target weight increase (in kg) to the required EMS intensity (in mA or %). This finding is particularly noteworthy as it aligns more closely with the literature on the perception of muscular effort than with psychophysical power laws of heaviness. This work also indicates that a "one-size-fits-all" approach is insufficient, as the exploratory correlations between individual user characteristics and perceptual outcomes support a case for personalization.

In conclusion, by establishing these foundational guidelines for ergonomic design and quantifying the perceptual response to EMS, this work creates a practical framework for developing more effective haptic systems. However, this investigation was conducted in haptic isolation, which directly motivates the final phase of this research: to understand how these principles integrate with visual feedback in a fully immersive environment.

7 Empirical Study 3: Visuohaptic Integration for EMS-Based Weight Perception

This third and final empirical chapter builds directly upon the findings of the preceding studies. The first empirical study established two foundational principles: first, that a synergistic dual-muscle EMS strategy is significantly more realistic and effective than a single-muscle approach (Part A), and second, that ML models can feasibly be used to personalize this feedback based on user-specific characteristics (Part B). The second empirical study then quantified the key factors that moderate this perception. First, it demonstrated that ergonomics are critical for perceived realism. Second, it showed that augmentation parameters—such as using a 3 kg base weight, which was found to be highly realistic—significantly influence the perceived realism of the sensation. Finally, it also characterized the quantitative function mapping a target weight increase to the required EMS intensity.

However, these investigations were conducted in haptic isolation. VR is an inherently multisensory medium, and a critical gap remains in understanding how this optimized EMS-based haptic feedback integrates with corresponding visual stimuli. The interplay between vision and haptics is complex; while visual dominance can be so powerful that it overshadows subtle haptic cues, posing a significant challenge for balancing sensory inputs in VR (Salvendy, 2012; Stellmacher et al., 2022), the specific effects of congruent and incongruent visuohaptic feedback for EMS-based weight rendering have not been systematically investigated.

Having explored what to stimulate (dual muscles), how to personalize it (with ML models), and how to modulate the intensity (the kg-to-EMS relationship), this thesis moves to the final stage of inquiry. This chapter details the design and execution of an experiment that systematically investigates this visuohaptic interplay. It will begin by outlining the study's objectives and hypotheses, followed by a comprehensive description of the methodology, a presentation of the results, and a discussion of their implications

for designing immersive visuohaptic experiences.

7.1 Objective and Hypotheses

The primary objective of this third and final empirical study is to systematically investigate the effects of congruent and incongruent visuohaptic feedback on both subjective user perception and objective motor behavior. The study is designed to isolate the distinct and combined contributions of EMS-based haptic feedback and visual feedback to create a comprehensive understanding of their interplay.

This investigation was guided by the following hypotheses, which translate the theoretical requirements for Object Presence (Section 2.1.2), the mechanisms of sensory dominance and prediction mismatch (Section 2.4.3), and the established coupling between perception and motor kinematics (Section 2.2.5)—employing the mixed-methods evaluation framework (objective vs. subjective) synthesized in Section 3.3—into specific empirical hypotheses:

H3.1: Congruence & Presence: The congruent visuohaptic condition, where visual and haptic feedback are synchronized, will yield significantly higher ratings for perceived realism and presence (assessed via the Igroup Presence Questionnaire, IPQ) compared to all other conditions.

H3.2: Haptic vs. Visual Realism: The haptic-only condition will be perceived as a more realistic simulation of weight change than the visual-only condition, highlighting the importance of proprioceptive cues.

H3.3: Perceptual Dissonance: The visual-only condition will generate the highest ratings for visuohaptic discrepancy, reflecting the sensory conflict between seeing a change in weight but not feeling one.

H3.4: Behavioral Adaptation: The congruent condition will lead to the most stable motor behavior (lowest intra-stimulus jerk), while the visual-only condition will lead to the least stable behavior (highest jerk), reflecting motor surprise from the sensory mismatch.

7.2 Method

The methodology for this study builds upon the common framework detailed in the ‘Overall Research Methodology’ chapter (Chapter 4). This section describes the specific

participants, apparatus, design, and procedures unique to this final investigation into visuohaptic feedback.

7.2.1 Participants

A total of N = 36 participants (24 male, 12 female), with a mean age of 23.5 years (SD = 4.26), were recruited for this study. The standardized recruitment, screening protocols, and the specific a priori power analysis used to determine this sample size are detailed in the 'Overall Research Methodology' chapter (see Section 4.2). All participants provided written informed consent and were compensated with 15€ for their participation in the approximately one-hour session.

7.2.2 Apparatus and Materials

The core EMS and control system (HASOMED© P24 device, axion electrodes, control laptop) are detailed in the 'Overall Research Methodology' chapter (see Section 4.3). For this study, the core EMS system was integrated with a full VR environment rendered on a MQ3 headset. The primary interactive object was a physical dumbbell, to which a MQ3 controller was securely mounted. This allowed the virtual representation to function as a high-fidelity "digital twin", with its position and orientation precisely co-located with the physical object.

7.2.3 Experimental Design

The study employed a 2x2 factorial within-subject design. The two independent variables, each with two levels, were:

- Haptic Feedback: ON (EMS applied) vs. OFF (no EMS)
- Visual Feedback: ON (visual size of the virtual object doubled) vs. OFF (visual size remained static)

The combination of these factors resulted in the four experimental conditions: Congruent Visuohaptic, Haptic-Only, Visual-Only, and Baseline. The presentation order of these four conditions was counterbalanced across participants using a balanced Latin Square design. This ensured that each of the four conditions appeared in each of the four trial positions (first, second, third, or fourth) exactly nine times, mitigating potential learning or ordering effects.

7.2.4 Procedure

The experimental session followed the standardized procedure for participant preparation and EMS calibration outlined in Section 4.4. Following calibration, participants were familiarized with the VR environment. The experimental task required participants to hold the controller-equipped dumbbell, which had a physical base weight of 3 kg, steady at a 90-degree elbow angle while viewing its virtual representation. This base weight was specifically chosen because the second empirical study identified the 3 vs 5 kg pair (a 3 kg base with a +2 kg augmentation) as one of the most realistic combinations.

In each of the four counterbalanced trials, one of the experimental conditions was triggered. For conditions involving a change, the stimuli were ramped up over a 10-second period. In the visual conditions (Visual-Only and Congruent), this involved the virtual dumbbell's size doubling (+100%). In the haptic conditions (Haptic-Only and Congruent), this involved the EMS intensity increasing to a peak of 60% of each participant's individual dynamic range [MT, PT]. This 60% level was chosen based on the findings from the second study to simulate a clearly perceptible weight increase of approximately +3 kg, creating a haptic stimulus designed to perceptually match the visual cue of the object doubling in size.

7.2.5 Dependent Measures

A mixed-methods approach was used to collect both subjective and objective data immediately following each trial.

- Subjective Measures: Participants completed the IPQ and a set of custom-developed, 7-point Likert scales (see Appendix D.3) to assess perceived realism, perceived weight change, visuohaptic discrepancy, and sense of agency.
- Objective Measure: The single objective measure was post-perturbation stability, operationalized as the movement jerk calculated from the VR controller's kinematic data recorded during and immediately after the stimulus event.

To operationalize post-perturbation stability, the movement jerk was calculated from the controller's kinematic data. The analysis was based on the velocity vector ($\vec{v} = [v_x, v_y, v_z]$) and the high-precision timestamp recorded for each sample. First, the instantaneous acceleration vector ($\vec{a}$) was numerically derived by calculating the first derivative of the velocity vector with respect to time (t). Subsequently, the instantaneous jerk vector ($\vec{j}$) was derived by calculating the first derivative of the resulting acceleration vector.

The scalar magnitude of the jerk at each time point, $||\vec{j}(t)||$, was then computed as the Euclidean norm: $\sqrt{j_x(t)^2 + j_y(t)^2 + j_z(t)^2}$. Finally, the single dependent measure used for the statistical analysis was the mean of this jerk magnitude, averaged over the entire 10-second duration of each trial.

7.2.6 Covariate Measures

To account for individual differences, a comprehensive set of covariates was measured prior to the experiment. These were grouped into three categories:

- Demographic Data: Age and sex.
- Physical Characteristics: Dominant arm, body weight and height, upper arm length, forearm length, upper arm circumference, and grip strength (measured with a hand dynamometer).
- EMS Thresholds: Each participant's individual ST, MT, and PT for both the triceps brachii and extensor carpi ulnaris muscles.

7.3 Results

7.3.1 Custom Questionnaire

To analyze the subjective data from the custom questionnaire, a series of 2 (Haptic Feedback: ON vs. OFF) x 2 (Visual Feedback: ON vs. OFF) repeated measures ANOVAs were conducted. Since all factors had only two levels, the assumption of sphericity was met by definition. The significance level was set at $\alpha = .05$. A summary of the descriptive statistics for all measures is presented in Table 7.1. The distributions of the Likert-scale ratings and the estimated weight increase are visualized in Figure 7.1 and Figure 7.2, respectively.

Perceived Weight Change

The analysis of perceived weight change revealed a significant main effect of Haptic Feedback, $F(1, 35) = 157.75, p < .001, \eta_g^2 = .57$, indicating that activating EMS led to a significantly stronger sensation of weight change. There was also a significant main effect of Visual Feedback, $F(1, 35) = 6.90, p = .013, \eta_g^2 = .03$, suggesting that the change in the object's size also contributed to the perception of weight change. No significant

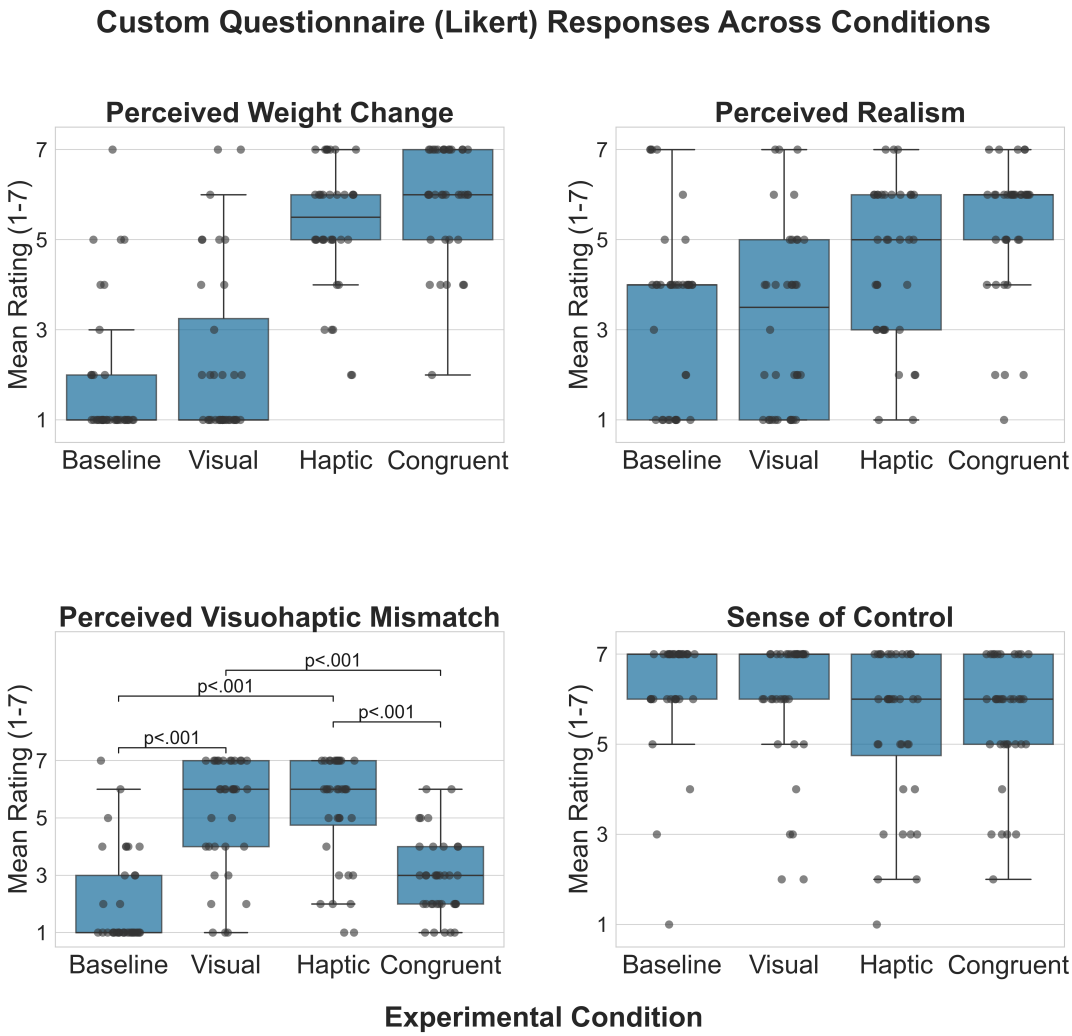


Figure 7.1: Boxplots showing the mean ratings for the four Likert-scale questionnaire items (A1-A4) across the four experimental conditions. Individual data points are also shown. Significance bars indicate Bonferroni-corrected pairwise comparisons ($p < .05$).

interaction effect was found between Haptic and Visual feedback, $F(1, 35) = 0.04, p = .841, \eta_g^2 < .001$.

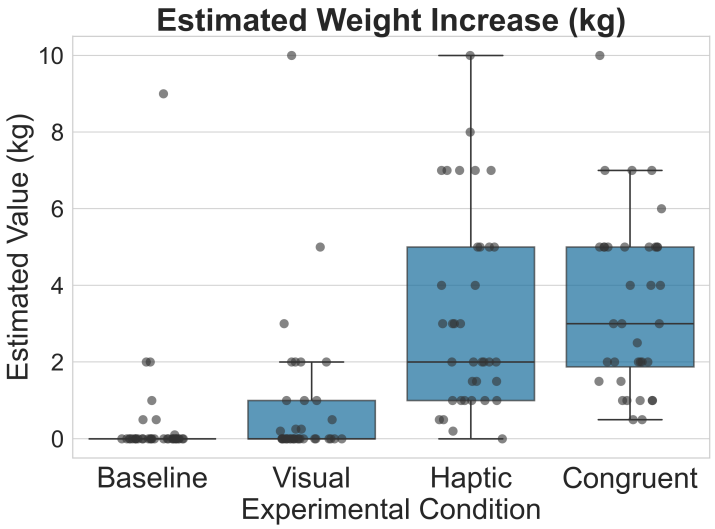


Figure 7.2: Boxplot showing the estimated weight increase (kg) (Item A5) across the four experimental conditions. Individual data points are also shown. Significance bars indicate Bonferroni-corrected pairwise comparisons ($p < .05$).

Perceived Realism of Weight Change

For the perceived realism ratings, there was a significant main effect of Haptic Feedback, $F(1, 35) = 19.87, p < .001, \eta_g^2 = .16$. Conditions with haptic feedback were rated as significantly more realistic. The main effect of Visual Feedback was not significant, $F(1, 35) = 1.92, p = .175, \eta_g^2 = .005$. Similarly, the interaction effect was not significant, $F(1, 35) = 3.40, p = .074, \eta_g^2 = .02$.

Perceived Visuohaptic Mismatch

The analysis of perceived visuohaptic mismatch revealed a highly significant interaction effect between Haptic and Visual feedback, $F(1, 35) = 66.27, p < .001, \eta_g^2 = .39$. The main effects for Haptic feedback, $F(1, 35) = 3.97, p = .054, \eta_g^2 = .02$, and Visual feedback, $F(1, 35) = 2.94, p = .095, \eta_g^2 = .01$, were not significant.

To decompose the significant interaction, Bonferroni-corrected pairwise comparisons were conducted across the four conditions. The results showed that the Visual-Only condition produced significantly higher mismatch ratings compared to the Baseline ($t(35) = 7.34, p < .001$, Hedges'$g = 1.71$) and Congruent ($t(35) = 5.35, p < .001$, Hedges'$g = 1.35$) conditions. Similarly, the Haptic-Only condition generated significantly higher mis-

Table 7.1: Descriptive Statistics (Mean and Standard Deviation) for Custom Questionnaire Items Across All Four Conditions.

Measure	Baseline $M(SD)$	Visual-Only $M(SD)$	Haptic-Only $M(SD)$	Congruent $M(SD)$
Weight Change	1.83 (1.56)	2.31 (1.91)	5.33 (1.41)	5.89 (1.24)
Realism	3.47 (1.93)	3.22 (2.02)	4.50 (1.73)	5.28 (1.52)
Mismatch	2.06 (1.66)	5.19 (1.97)	5.28 (1.91)	2.89 (1.37)
Control	6.28 (1.28)	6.00 (1.47)	5.33 (1.71)	5.56 (1.38)
Weight Estimate (kg)	0.42 (1.55)	0.84 (1.91)	3.24 (2.60)	3.51 (2.26)

match ratings than the Baseline ($t(35) = 8.29, p < .001,$ Hedges'$g = 1.79$) and Congruent ($t(35) = 6.31, p < .001,$ Hedges'$g = 1.42$) conditions. There was no significant difference in mismatch ratings between the Haptic-Only and Visual-Only conditions ($t(35) = 0.26, p > .99$), nor between the Baseline and Congruent conditions ($t(35) = 2.65, p = .073$).

Sense of Control

For the sense of control, a significant main effect was found for Haptic Feedback, $F(1, 35) = 15.14, p < .001, \eta_g^2 = .05$, where conditions with haptics were associated with a significantly lower level of perceived control. The main effect of Visual Feedback was not significant, $F(1, 35) = 0.02, p = .887, \eta_g^2 < .001$, and there was no significant interaction effect, $F(1, 35) = 1.15, p = .290, \eta_g^2 = .007$.

Estimated Weight Increase (kg)

Finally, for the estimated weight increase, the analysis showed a significant main effect of Haptic Feedback, $F(1, 35) = 52.37, p < .001, \eta_g^2 = .30$, and a significant main effect of Visual Feedback, $F(1, 35) = 4.42, p = .043, \eta_g^2 = .007$. Participants estimated a greater increase in weight when haptic and visual cues were present. There was no significant interaction effect, $F(1, 35) = 0.18, p = .675, \eta_g^2 < .001$.

7.3.2 Presence (IPQ)

To assess the influence of the feedback conditions on the sense of presence, a 2x2 repeated measures ANOVA was conducted on the four sub-scales of the IPQ. Since all factors

had only two levels, the assumption of sphericity was met by definition. Descriptive statistics are summarized in Table 7.2, and the distribution of ratings across conditions is visualized in Figure 7.3.

Table 7.2: Descriptive Statistics (Mean and Standard Deviation) for IPQ Sub-scales Across All Four Conditions.

IPQ Sub-scale	Baseline $M(SD)$	Visual-Only $M(SD)$	Haptic-Only $M(SD)$	Congruent $M(SD)$
General Presence	3.92 (1.61)	3.75 (1.71)	3.61 (1.79)	4.17 (1.80)
Spatial Presence	3.69 (0.86)	3.61 (0.79)	3.34 (1.02)	3.74 (0.85)
Involvement	2.76 (1.05)	2.94 (0.85)	2.88 (0.91)	3.01 (0.95)
Experienced Realism	2.15 (1.21)	1.86 (1.01)	1.97 (1.15)	2.51 (1.21)

General Presence

For the General Presence sub-scale, which measures the core sense of "being there", the analysis revealed no significant main effect of Haptic Feedback, $F(1, 35) = 0.14, p = .714, \eta_g^2 < .001$, or Visual Feedback, $F(1, 35) = 1.16, p = .289, \eta_g^2 = .003$. The interaction effect was also not significant, $F(1, 35) = 3.93, p = .055, \eta_g^2 = .011$.

Spatial Presence

The analysis of the Spatial Presence sub-scale revealed a significant interaction effect between Haptic and Visual feedback, $F(1, 35) = 6.94, p = .012, \eta_g^2 = .019$. Neither of the main effects was significant. To decompose the interaction, Bonferroni-corrected pairwise comparisons were conducted. The results showed that the Congruent condition ($M = 3.74, SD = 0.85$) yielded significantly higher Spatial Presence ratings than the Haptic-Only condition ($M = 3.34, SD = 1.02$), $t(35) = 2.80, p = .049$, Hedges'$g = 0.43$. No other comparisons were statistically significant.

Involvement

For the Involvement sub-scale, which reflects the user's captivation by the virtual experience, there were no significant main effects for Haptic Feedback, $F(1, 35) = 0.94, p = .338, \eta_g^2 = .002$, or Visual Feedback, $F(1, 35) = 2.84, p = .101, \eta_g^2 = .007$. The interaction effect was also not significant, $F(1, 35) = 0.06, p = .811, \eta_g^2 < .001$.

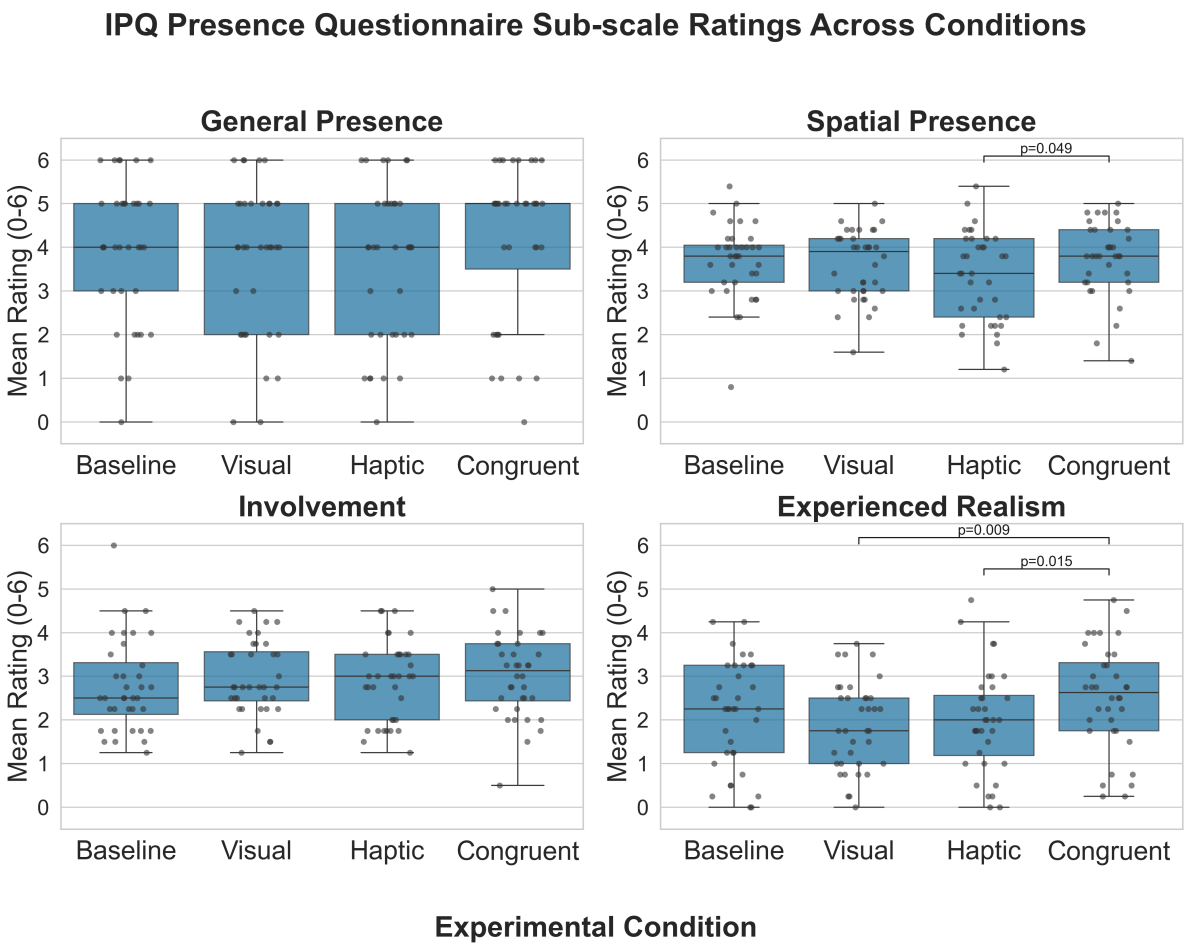


Figure 7.3: Boxplots showing the mean ratings for each IPQ sub-scale across the four experimental conditions. Individual data points are also shown. Significance bars indicate Bonferroni-corrected pairwise comparisons ($p < .05$).

Experienced Realism

The analysis of the IPQ's Experienced Realism sub-scale showed a significant main effect for Haptic Feedback, $F(1, 35) = 5.43, p = .026, \eta_g^2 = .011$, and a highly significant interaction effect between Haptic and Visual feedback, $F(1, 35) = 10.77, p = .002, \eta_g^2 = .032$. The main effect for Visual Feedback was not significant, $F(1, 35) = 1.80, p = .188, \eta_g^2 = .003$. Bonferroni-corrected pairwise comparisons to break down the interaction

revealed that the Congruent condition ($M = 2.51, SD = 1.21$) was rated as significantly more realistic than both the Haptic-Only condition ($M = 1.97, SD = 1.15$), $t(35) = 3.25, p = .015$, Hedges'$g = 0.45$, and the Visual-Only condition ($M = 1.86, SD = 1.01$), $t(35) = 3.44, p = .009$, Hedges'$g = 0.57$.

7.3.3 Exploratory Correlation Analysis of Participant Covariates

To explore potential relationships between participant characteristics and their overall experience, a Pearson correlation analysis was conducted. For this analysis, each participant's mean rating across all four conditions was calculated for the nine primary subjective outcome measures (five from the custom questionnaire and four from the IPQ). These aggregated scores were then correlated with the fifteen demographic, physical, and EMS-related covariates (Figure 7.4). A total of 135 individual correlations were evaluated. At an α level of .05, approximately 6-7 false positives would be expected by chance alone. Because only five correlations reached nominal significance, they are no longer statistically significant after applying a Benjamini-Hochberg False Discovery Rate correction (Benjamini & Hochberg, 1995). Consequently, these findings are reported strictly as an exploratory analysis rather than definitive evidence. Prior to correction, the analysis revealed five nominally significant correlations.

A significant negative correlation was found between Grip Force and the perceived magnitude of weight change ($r = -0.34, p = .045$), suggesting that participants with stronger grip strength tended to perceive the EMS-induced weight change as less significant overall. Furthermore, participants' overall sense of control was positively correlated with their upper arm PT ($r = 0.36, p = .032$) and lower arm PT ($r = 0.34, p = .046$), indicating that individuals with higher PT reported a greater sense of control during the experiment.

Finally, the IPQ Involvement sub-scale was significantly and positively correlated with both Grip Force ($r = 0.44, p = .007$) and Lower Arm Length ($r = 0.40, p = .015$). This suggests that participants with greater grip strength and longer lower arms reported feeling more captivated and involved in the virtual experience. No other covariates showed a significant linear relationship with the aggregated outcome measures.

7.3.4 Objective Motor Behavior (Intra-Stimulus Jerk)

To test the hypothesis (H3.4) that feedback conditions would influence motor stability, a 2 (Haptic Feedback: ON vs. OFF) x 2 (Visual Feedback: ON vs. OFF) repeated measures ANOVA was conducted on the mean intra-stimulus movement jerk

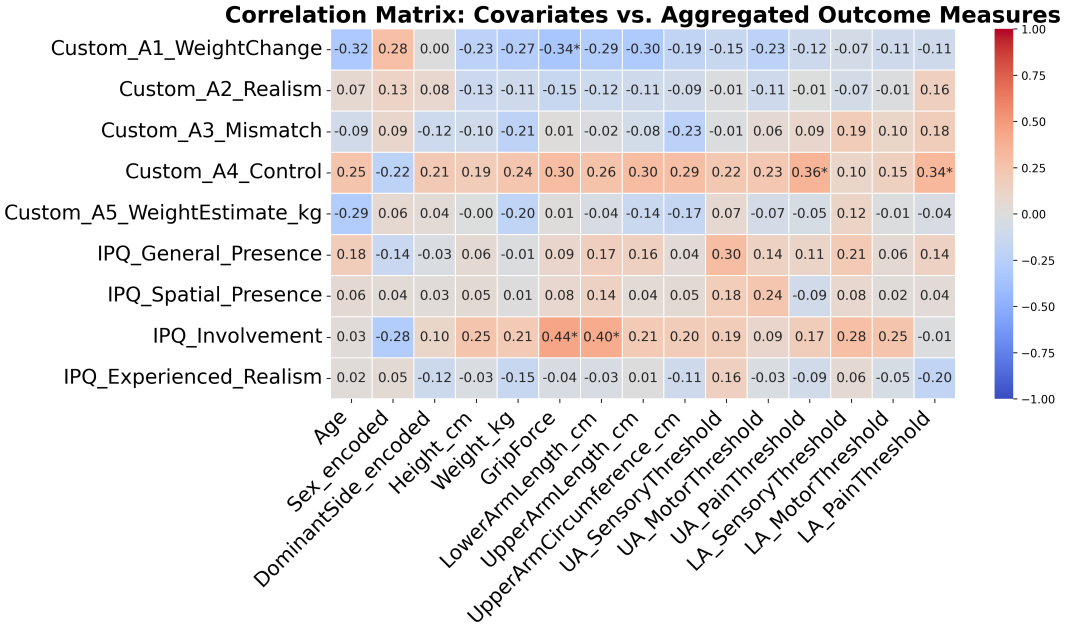


Figure 7.4: Heatmap of Pearson correlations between participant covariates and aggregated subjective outcome measures. Asterisks indicate statistical significance ($p < .05$).

for the complete dataset of N=36 participants. Since all factors had only two levels, the assumption of sphericity was met by definition. The analysis revealed no significant main effect of Haptic Feedback, $F(1, 35) = 1.57, p = .219, \eta_g^2 = .006$, and no significant main effect of Visual Feedback, $F(1, 35) = 0.18, p = .676, \eta_g^2 < .001$. Furthermore, there was no significant interaction effect between Haptic and Visual feedback, $F(1, 35) = 1.73, p = .197, \eta_g^2 = .003$.

These results indicate that the different feedback conditions did not produce statistically significant differences in motor stability as measured by jerk. Therefore, the data do not support hypothesis H3.4. A summary of the descriptive statistics is presented in Table 7.3 and the distribution of jerk values is visualized in Figure 7.5.

Table 7.3: Descriptive Statistics (Mean and Standard Deviation) for Intra-Stimulus Movement Jerk Across All Four Conditions (N=36).

Measure	**Baseline** $M(SD)$	**Visual-Only** $M(SD)$	**Haptic-Only** $M(SD)$	**Congruent** $M(SD)$
Mean Jerk (m/s^3)	12.48 (5.82)	13.00 (7.50)	14.23 (7.53)	13.22 (5.09)

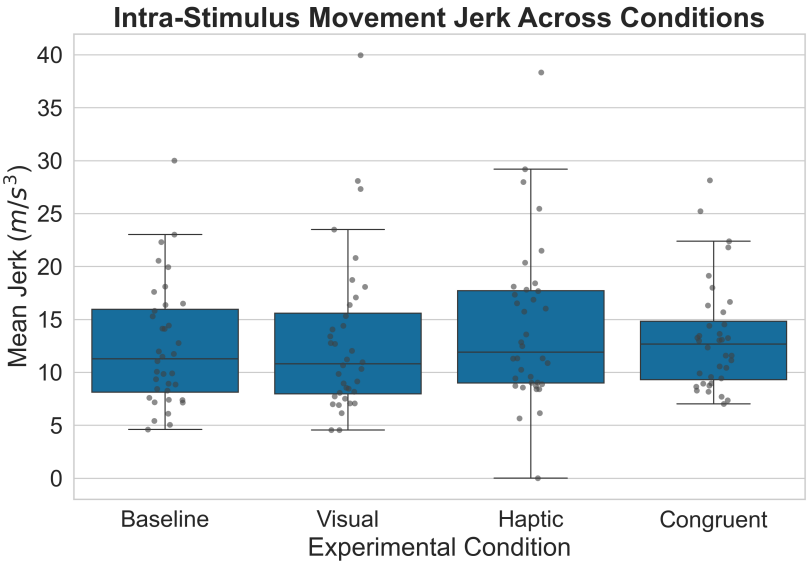


Figure 7.5: Boxplot showing the mean intra-stimulus movement jerk across the four experimental conditions. Individual data points are also shown.

7.4 Discussion

This final empirical study was designed to investigate the interplay between EMS-based haptic feedback and visual feedback when rendering weight in a virtual environment. The findings provide a nuanced understanding of how multisensory integration influences user perception and behavior, offering clear, evidence-based guidelines for designing immersive experiences.

The results largely support the primary hypothesis (H3.1) that congruent visuohaptic feedback is superior. Across the subjective measures, the Congruent condition consistently produced the highest ratings for perceived realism and presence. This effect was statistically significant for the IPQ's Experienced Realism and Spatial Presence sub-

scales, confirming that the synchronized combination of seeing and feeling a change in weight creates a more realistic and spatially coherent virtual world than either modality in isolation. However, broader measures like general presence and involvement were not significantly affected. This divergence from the general expectation that haptics universally elevate presence likely occurred because all conditions involved grasping a physical proxy; this anchored the baseline sense of general presence, leaving the congruent EMS to primarily refine spatial realism rather than overall immersion. This underscores a key principle for haptic design: fidelity is not just about the quality of a single sensory channel, but about the coherence of the entire multisensory experience—a finding that aligns directly with the theoretical premise that ambiguous or conflicting haptic sensations risk breaking immersion by drawing the user's attention to the physical interface (Gao & Spence, 2025).

Furthermore, the data clearly supports the hypothesis (H3.2) that haptic feedback is the primary driver of perceived weight change and realism. The analyses of Perceived Weight Change, Estimated Weight Increase, and the custom Realism scale all revealed a large and significant main effect of Haptic Feedback. In contrast, the main effect of Visual Feedback was either weaker or non-significant for these measures. This suggests that while seeing an object grow larger can influence the perception of weight, the proprioceptive sensation generated by EMS is the dominant and most convincing cue for this specific task. This finding parallels the principle of tactile dominance observed in phenomena like the Material-Weight Illusion, where physical haptic cues effectively override conflicting visual input (Naylor et al., 2022). Furthermore, it reinforces the core physiological theory that the human judgment of heaviness is inherently tied to the sense of muscular effort and central motor commands, rather than purely visual estimations (Jones, 1986; Proske & Gandevia, 2012). Notably, the participants' explicit weight estimates provide further validation for the EMS parameters used. The mean estimated weight increase in the Haptic-Only (3.24 kg) and Congruent (3.51 kg) conditions closely matched the intended simulation target of approximately 3 kg, which was based on the EMS intensity scaling derived from Study 2 (see Figure 6.9). This close agreement demonstrates the effectiveness of the calibration and scaling methodology. This finding supports the main idea of this thesis: for interactions involving physical effort, rendering convincing haptic feedback is not just an enhancement but a basic requirement for perceived realism. This strong haptic effect was not without a minor trade-off, however, as the analysis also revealed a significant main effect of Haptic Feedback on 'Sense of Control,' indicating that activating EMS was associated with a slightly lower level of perceived control.

The analysis of visuohaptic mismatch provides a clear explanation for these findings

and offers partial support for H3.3, while refining its specifics. Both the Visual-Only and Haptic-Only conditions produced significantly high levels of perceived mismatch compared to congruent or baseline conditions, quantitatively demonstrating the perceptual dissonance that occurs when the senses are in conflict. Much like the prediction mismatch theory underlying the Size-Weight Illusion—where visual expectations fail to align with haptic reality (Jones, 1986; van Polanen & Davare, 2019)—this EMS-induced mismatch shatters the perceptual illusion. Crucially, both incongruent conditions were rated equally high in mismatch, indicating that any conflict (visual without haptic, or haptic without visual cause), not just the visual-only case originally hypothesized, creates a powerful sense of perceptual dissonance. While typical visual-dominance theories suggest vision overshadows haptics, those models generally apply when haptic cues are subtle (Stellmacher et al., 2022). The EMS applied here, however, generated a strong haptic sensation. Because the haptic channel naturally dominates weight judgment (Naylor et al., 2022), feeling such an intense physical change without a visual update triggers a severe prediction mismatch (Jones, 1986; van Polanen & Davare, 2019), violating fundamental physical expectations just as strongly as a visual change without a haptic consequence. This finding highlights the cost of incongruence: while unimodal feedback can convey information, it does so at the risk of breaking the user's sense of presence by creating an unnatural sensory conflict.

Interestingly, the hypothesis regarding motor behavior (H3.4) was not supported, as the analysis revealed no significant differences in intra-stimulus jerk across the four conditions. This null finding contrasts with the principle discussed previously (see Section 2.2.5), where motor kinematics in dynamic tasks often serve as reliable proxies for perception (Moosavi et al., 2024). For the quasi-static holding task used here, however, jerk appears insensitive to the subtle compensatory adjustments participants likely made to maintain stability despite the perceptual conflict indicated by the mismatch ratings. A probable physiological explanation for this contrast is that maintaining a static posture requires continuous muscle co-contraction; this inherently increases joint stiffness and naturally dampens the high-frequency kinematic fluctuations that jerk metrics are designed to capture. While the principle that motor control adapts to perception remains valid, jerk during this specific static task did not provide the objective correlate that lifting kinematics might in more dynamic scenarios. Further work using different tasks or measures like EMG may be needed to capture behavioral effects related to visuohaptic incongruence with EMS.

Finally, the exploratory correlation analysis provides a nuanced look at how individual differences may scale with the user experience. While the following relationships did not survive a Benjamini-Hochberg correction for the 135 tests conducted—and thus must be

interpreted as tentative trends—they align with the individual variability observed in Study 2. Prior to correction, a significant relationship was observed where participants with stronger Grip Force, for instance, perceived the weight change as less significant but also reported higher IPQ Involvement. This is consistent with prior research indicating that natural haptic force control and steadiness are heavily predicted by absolute strength and distinct neural control strategies (Brown et al., 2010). This latter finding, along with a positive correlation for Lower Arm Length, suggests certain physical metrics may predict user engagement. Furthermore, the observation that participants with a higher PT reported a greater sense of control suggests that a wider functional dynamic range may be critical for maintaining user agency. When individuals can tolerate stronger EMS without it becoming painful, the system can render more robust forces without breaking the weight illusion. This indicates that avoiding pain is not merely a matter of user comfort, but a fundamental prerequisite for seamless sensorimotor integration; if the EMS feels like an external electrical shock rather than internal muscular effort, the haptic experience fails. These observations once again underscore the potential necessity of personalized calibration and adaptive systems to account for the unique characteristics of each user, reaffirming the broad consensus in haptic research that a "one-size-fits-all" approach is fundamentally flawed (Seifi, 2019).

In sum, this study demonstrates that while haptics provides the foundation for perceived realism, it is the congruent marriage of haptic and visual feedback that creates a truly immersive and realistic weight sensation. The following chapter will synthesize these findings with those from the preceding studies to propose a comprehensive framework for personalized, multimodal weight rendering in VR.

7.5 Interim Conclusion

This final empirical study has provided critical insights into the multisensory integration of EMS-based haptic feedback for weight perception in VR. The findings demonstrate that while haptic feedback provides the foundation for perceived realism, it is the congruent marriage of haptic and visual feedback that creates a truly realistic weight sensation.

The results offer substantial support for the core hypotheses. In alignment with H3.1, congruent visuohaptic feedback was shown to be superior, significantly enhancing the perceived realism and spatial presence of the experience. As predicted by H3.2, haptic feedback emerged as the dominant modality for judging the magnitude and realism of the weight change. This was powerfully demonstrated by participants' weight estimates, which closely matched the intended 3 kg target and thereby validated the respective

results from Study 2. H3.3 was partially supported; the results revealed that any sensory conflict—not just a visual one—induces a significant sense of mismatch, as salient haptic cues proved resistant to visual overshadowing. While the perceptual effects were clear, H3.4 was not supported, as no significant differences in motor jerk were found, suggesting that behavioral reactions to sensory conflict in quasi-static tasks may be too subtle for this measure. Finally, exploratory correlations suggested that individual physical traits may influence engagement and control, though these observations remain tentative as they did not survive multiple comparisons correction.

By providing the necessary multimodal context for the haptic principles established in the preceding chapters, this study provides the final piece of empirical evidence for this thesis. The research can now move from analysis to synthesis, connecting the findings from all three studies to build a comprehensive framework for personalized weight rendering.

8 General Discussion and Synthesis

8.1 Synthesis of Key Findings Across Studies

The scientific work reported in this thesis aimed at addressing these research gaps by developing a framework for rendering realistic weight sensations with personalized EMS. This work was built upon four pillars, beginning with a systematic literature review that identified critical gaps in the existing research. The review revealed a promising but fragmented field lacking methodological consensus and a deep understanding of the factors governing perceived realism and personalization. To address these gaps, a three-part empirical investigation was designed, with each study building logically upon the last. The first study established a foundational EMS strategy. The second study quantified the key moderating factors for that strategy. The third and final study integrated this knowledge into a complete multisensory context. The findings from these interconnected studies cumulatively provide a clear, evidence-based pathway from basic EMS principles to effective multimodal haptic design.

The first empirical pillar of this thesis established a foundational EMS strategy and provided a direct, data-driven path toward its personalization. The first empirical study (Part A) provided the first systematic, quantitative evidence that a synergistic, dual-muscle approach is fundamentally superior to the single-muscle methods common in earlier literature (Faltaous et al., 2022; Galofaro et al., 2022). It demonstrated that applying EMS to both the triceps brachii and the extensor carpi ulnaris was not only rated as significantly more realistic but was also quantitatively more efficient, requiring less current to achieve the same perceptual increase in weight as measured by the PSE. This finding empirically validates the qualitative feedback from prior studies (Galofaro et al., 2022), moving beyond the binary feedback limitations of earlier systems (Lopes et al., 2017, 2018). Having established a superior technique, the study (Part B) then addressed the challenge of inter-subject variability by demonstrating a viable, data-driven path to personalization. The development of predictive models, which achieved F1-scores of up to 77% in predicting perceptual outcomes, provided a preliminary proof-of-concept for an adaptive system—signaling a definitive move away from the static

parameters identified as a critical limitation in the systematic review.

Second, the research provided the deep quantification necessary to validate and implement this personalized approach. The second empirical study indicated the need for personalization, suggesting that a "one-size-fits-all" approach to the dual-muscle technique is insufficient. This study systematically quantified why personalization is needed, revealing that ergonomics matter, with neutral holding postures like a 90° elbow angle yielding significantly higher perceived realism. The study also identified a perceptual optimum for weight augmentation (+2 kg) and indicated that individual user characteristics are associated with perceptual outcomes: age and BMI with perceived realism, and grip strength with the required EMS intensity. This finding supports the need for personalization called for in the broader haptics literature (Kotian & Nandipi, 2024; Seifi, 2019) and motivates the ML approach demonstrated in the first study.

Finally, this thesis situated these haptic principles within the broader context of immersive virtual environments by investigating the role of multisensory integration. The third empirical study confirmed that congruent visuohaptic feedback is essential for maximizing perceived realism and presence. The synchronized combination of seeing an object grow larger while feeling the corresponding increase in weight was the only feedback condition that did not create a significant sense of visuohaptic mismatch; it was rated as significantly more realistic and immersive than either the haptic or visual cue in isolation. The data also suggested that for this task, haptic feedback—rooted in the sense of effort (Proske & Gandevia, 2012)—was the dominant sense for determining the magnitude and realism of the weight change. Interestingly, the expected effects on objective motor behavior (jerk) were not observed. This suggests that in quasi-static tasks, the kinematic dampening caused by muscle co-contraction may mask the behavioral correlates of sensory conflict, even when that conflict is clearly perceived subjectively.

In essence, the four pillars of this thesis—the literature review (Vrontos et al., 2024) and the three sequential empirical studies—provide a clear, evidence-based framework. The findings show that to create a realistic haptic experience, one should begin with a dual-muscle EMS strategy, optimize it by considering ergonomic best practices, and account for individual differences in physical traits. Finally, these haptic elements must be integrated congruently with visual feedback to avoid perceptual dissonance. These three interconnected studies provide the evidence for a comprehensive, four-tiered framework—detailed in the following section—that moves the field from isolated proofs-of-concept toward a principled methodology for designing truly immersive haptic interactions.

8.2 A Framework for Personalized EMS-Based Weight Feedback

The central contribution of this thesis is the development of a comprehensive, evidence-based framework for creating realistic and personalized EMS-based weight feedback. This framework synthesizes the key findings from the three empirical studies into a prescriptive, four-tiered model that guides researchers and designers from foundational principles to full multisensory integration. Each tier builds upon the last, addressing a critical aspect of the haptic rendering process.

8.2.1 Tier 1: The Foundational Principle - Synergistic Muscle Actuation

The first and most fundamental principle, established in the first empirical study, is that realistic weight rendering requires a synergistic, dual-muscle EMS strategy. The findings provided the first quantitative evidence that stimulating both the triceps brachii and the extensor carpi ulnaris is significantly superior to stimulating the triceps alone. This approach was not only rated as substantially more realistic, but it was also more efficient, requiring significantly less current to produce the same perceptual effect. This principle is grounded in biomechanics; by engaging muscles that control both the elbow and the wrist, the EMS more closely mimics the body's natural, distributed response to handling a physical load. Therefore, any system aiming for realistic weight feedback should begin with a multi-muscle EMS strategy as its foundation.

8.2.2 Tier 2: Individual Adaptation - Calibration and Personalization

With the foundational technique established, the next essential step is to tailor it to the individual user. The findings from all three studies converge on a single, unambiguous conclusion: a "one-size-fits-all" approach to EMS is insufficient, empirically confirming the need for personalization called for in the broader haptics literature (Kotian & Nandipi, 2024; Seifi, 2019). The framework's second tier addresses this necessity at two levels of sophistication.

- **Mandatory Baseline: Individual Calibration.** The most critical and non-negotiable step for any practical application is the personalized calibration of each

user's Motor and Pain Thresholds [MT, PT]. As shown in the correlation analyses, the absolute EMS intensity required for a user to perceive a specific target weight (the PSE) is strongly predicted by their PT. By operating on a normalized scale based on this calibrated dynamic range, a system can deliver perceptually consistent and safe feedback across users with vastly different sensitivities.

- **Advanced Personalization: Predictive Modeling.** The second part of the first study provided a proof-of-concept for a more advanced, data-driven approach. The development of predictive ML models, which predicted perceptual outcomes with F1-scores of up to 77%, demonstrates the feasibility of personalization. The feature importance analysis revealed that a robust model must integrate both the applied EMS parameters and the user's unique physiological characteristics, such as BMI and individual PTs. This paves the way for truly adaptive systems that can predict and deliver an optimal EMS profile for a new user based on their specific profile.

8.2.3 Tier 3: Contextual Optimization - Ergonomics and Augmentation

After personalizing the EMS to the individual, the framework's third tier addresses the context in which the haptic feedback is delivered. The second empirical study demonstrated that both the user's physical posture and the nature of the haptic effect itself are critical.

- **Ergonomics are paramount:** A user's posture directly impacts perceived realism. The findings showed that a perpendicular, 90° elbow angle was significantly more realistic than an acute 45° angle. This implies that haptic experiences should be designed around common, biomechanically stable postures to avoid introducing conflicting proprioceptive cues that can break the illusion.

- **A perceptual optimum for augmentation exists:** Perceived realism is not linear with EMS intensity. The study identified a perceptual optimum where a 2 kg augmentation was rated as most realistic. This highlights the principle of sensory congruence: the simulated weight increase must be plausible relative to the object's base weight to avoid creating a sensory conflict that undermines perceived realism.

8.2.4 Tier 4: Multisensory Integration - Visuohaptic Congruence

Finally, the haptic sensation does not exist in a vacuum. The third empirical study demonstrated that for the experience to be truly immersive, the haptic feedback must be coherently integrated with other sensory modalities. The final tier of the framework is the principle of visuohaptic congruence. The findings showed that the synchronized combination of seeing an object grow larger while feeling the corresponding increase in weight was the only feedback condition that did not create a significant sense of visuohaptic mismatch; it was rated as significantly more realistic and immersive than either modality in isolation. This confirms that fidelity is not a property of a single sensory channel, but an emergent property of the entire multisensory experience. To maximize immersion and avoid the perceptual dissonance that can shatter presence, EMS-based haptic events must be designed to be congruent with their visual counterparts–ensuring that the visual expectation of weight aligns perfectly with the haptic sense of effort.

8.3 The Role of Individual Characteristics in EMS Personalization

A central argument of this thesis is that effective haptic feedback cannot be a "one-size-fits-all" solution. The findings from all three empirical studies, when synthesized, provide a clear and data-driven verdict on the role of individual characteristics, justifying why personalization is not an optional feature but a foundational requirement. The evidence consistently clusters around three key categories of participant covariates: EMS sensitivity, anthropometric/physical build, and physical strength.

First, the most unambiguous finding across all studies is the critical role of individual EMS sensitivity, captured by the MT and PT. This factor is the primary determinant of EMS delivery and comfort. The second study provided the clearest evidence, showing that a participant's absolute PT was the single best predictor of the absolute current (mA) required to perceive a given weight, with correlations as high as $r = .87$. The first study (Part B) confirmed this, identifying Triceps PT, Triceps MT, and Extensor PT as essential predictive features for its ML models. Furthermore, the third study linked this to the subjective experience, finding that participants with higher pain thresholds reported a significantly greater overall sense of control. Taken together, these results confirm that individual calibration of the [MT, PT] dynamic range is the non-negotiable first step for any personalized EMS system.

Second, the findings demonstrate that a user's anthropometric and physiological char-

acteristics—such as BMI, age, and body dimensions—are independent and unique predictors of their subjective experience, not merely proxies for their individual sensitivity to EMS. The second study found that both Age and BMI were strong positive correlates of perceived realism, suggesting a user's physical build and age directly influence how believable they find the simulation. This was reinforced by the "EMS efficiency" analysis, which identified a clear profile of the most efficient user: an individual who was older and had a larger build (higher BMI, Weight, and Upper Arm Circumference). The first study's ML models further validate this, as they selected BMI and Forearm Length as crucial, independent features for predicting perceptual outcomes, separate from the EMS thresholds themselves.

Finally, physical strength, measured via Grip Force, revealed a more complex and nuanced role. It was simultaneously a predictor of relative sensitivity and subjective engagement. The second study found that stronger participants were more efficient, requiring a significantly smaller percentage of their dynamic range (Normalized Intensity, $r = -.52$) to perceive the target weight. This was complemented by the third study, where stronger participants perceived less overall weight change ($r = -0.34$), yet, paradoxically, also reported significantly higher IPQ Involvement ($r = .44$). This paints a complex picture where a user's strength influences their relative sensitivity while also potentially impacting their level of immersion.

In summary, the synthesis of these findings is unambiguous. The consistent, statistically significant, and non-obvious relationships between individual characteristics and experimental outcomes provide a robust, data-driven mandate for the framework's focus on personalization. The evidence confirms that to create an effective and realistic EMS-based haptic system, one must account for both the user's individual sensitivity (their EMS thresholds) and their unique physiological profile (their age, build, and strength).

8.4 Broader Implications for Design and Applications

The comprehensive framework developed in this thesis offers more than theoretical insight; it provides a set of practical, evidence-based guidelines that have significant implications for the design and application of future haptic systems. By shifting the focus from generic, "one-size-fits-all" feedback to user-specific, context-aware haptic rendering, the framework addresses key barriers to the widespread adoption and effectiveness of haptic technology. The findings directly inform the development of more effective and realistic interactions in immersive VR/AR, physical rehabilitation, and teleoperation.

8.4.1 A Methodological Blueprint for Replicable EMS Haptics

A primary contribution of this thesis, established first by the systematic literature review (Vrontos et al., 2024), is the identification of a critical methodological gap in the field: the pervasive lack of standardized and comprehensive reporting of EMS parameters. This ambiguity is a significant barrier to scientific progress, making the replication and comparison of studies nearly impossible.

In response to this gap, this thesis offers a direct solution by providing both a detailed, replicable methodology and a summarized, actionable tool. To support the adoption of new standards and provide a model for future work, a compact reporting protocol derived from the methods used throughout this research is presented in Appendix B.

The foundation for this protocol was a deliberate commitment to replicability, as detailed in the 'Overall Research Methodology' (Chapter 4). All three empirical studies were built upon a consistent and fully-disclosed framework encompassing not just the technology, but the entire experimental process. This included specifying all crucial parameters:

- A Standardized Technical Stack: A consistent hardware and software foundation was used, including a specific, computer-controlled EMS system (P24 Science, HASOMED© GmbH), precise electrode sizes (10x5 cm and 5x5 cm), and custom control software.
- A Fixed EMS Protocol: A physiologically-informed set of parameters was used across all studies, including a symmetrical biphasic rectangular pulse (to minimize tissue irritation (Bowman & Baker, 1985; Diamant & Reilly, 2011)), a 40 Hz frequency (to ensure a fused, tetanic contraction while mitigating fatigue (Behringer et al., 2016; Knibbe et al., 2018)), and a 120 µs pulse width (to provide a "neutral" sensation (Gracanin & Trnkoczy, 1975; Knibbe et al., 2018)).
- A User-Centric Calibration Method: A clear protocol defining that haptic intensity was exclusively modulated via current amplitude (mA), which was always normalized to each participant's individually calibrated dynamic range between their MTs and PTs. This crucial step ensures that feedback is both safe and perceptually comparable across individuals.
- A Robust Ethical and Safety Framework: All studies adhered to a strict protocol that included thorough participant screening based on health exclusion criteria, obtaining written informed consent under an approved ethics protocol, and implementing safety measures such as a user-controlled stop.

By providing this complete, replicable methodology, this thesis not only presents a set of empirical findings but also offers a solution to the field's replicability crisis. The evidence-based framework presented in this chapter is only as valuable as it is reproducible. Therefore, this work includes an implicit call for a new standard of methodological rigor. For the field to advance, it is crucial that future research adopts this level of comprehensive reporting.

8.4.2 Implications for Immersive VR/AR Experiences

For designers of immersive games, training simulations, and other virtual experiences, the findings provide a clear blueprint for rendering convincing weight and force. The quantitative proof that dual-muscle EMS is more realistic than the single-muscle approaches explored in foundational work (Faltaous et al., 2022; Galofaro et al., 2022) provides a core design principle: to make a virtual shield feel heavy or a virtual tool feel substantial, developers should target synergistic muscle groups. This moves beyond simply rendering binary force feedback (Lopes et al., 2017, 2018) towards more nuanced and realistic physical interactions. Furthermore, the emphasis on ergonomic factors (Study 2) suggests designing interactions around neutral holding postures, such as a 90° elbow angle, where the haptic illusion is strongest. The research also highlights the importance of sensory congruence not just in timing but also in magnitude; the identification of a perceptual optimum for weight augmentation (Study 2) implies that aiming for plausible, moderate force effects may be more effective for perceived realism than attempting extreme sensations. The critical role of visuohaptic congruence (Study 3) reinforces this, offering an unambiguous guideline: the haptic effect must be perfectly synchronized and plausibly matched with its visual counterpart. The research demonstrates that an incongruent stimulus is worse than no feedback at all, as it produces a perceptual dissonance that actively breaks presence. Finally, the effectiveness of the ML models (Study 1, Part B) paves the way for a future where VR/AR systems—whether for gaming (Khamis et al., 2019; Lopes & Baudisch, 2013) or training (Pfeiffer et al., 2019)—can run a brief, automated calibration routine to personalize the haptic experience, ensuring that every user, regardless of their physiology, experiences the intended effect with optimal perceived realism and intensity, potentially leveraging the quantified scaling relationship (Study 2) as a baseline.

8.4.3 Implications for Physical Rehabilitation and Physiotherapy

The principles of personalization and ergonomic optimization developed in this thesis have profound implications for therapeutic applications. The quantification of how individual characteristics like age, BMI, and strength predict EMS perception (Study 2) provides a data-driven foundation for creating safer and more precisely dosed rehabilitation programs. Instead of relying on less controllable tools like elastic bands, therapists could leverage a predictive model—like the one demonstrated feasible in Study 1 (Part B)—to administer a specific, repeatable, and quantifiable level of resistance or assistance, precisely tailored to a patient's evolving needs. This addresses a key challenge in physiotherapy: ensuring consistent therapeutic load. Furthermore, the discovery that ergonomics are critical to perceived realism informs the design of more effective therapeutic exercises. Virtual rehabilitation tasks can be designed to guide patients through movements within biomechanically optimal and comfortable ranges (e.g., around the 90° elbow angle), with personalized EMS providing appropriately scaled support or resistance. By making these often repetitive exercises more engaging and realistic through congruent visuohaptic feedback (as shown crucial in Study 3), this approach holds significant potential to improve patient motivation, adherence, and ultimately, therapeutic outcomes.

Beyond providing resistance, the principles of personalized EMS can be extended to deliver corrective haptic feedback for motor learning, akin to how EMS has been used in skill training (Ebisu et al., 2017). As demonstrated in a related project (Vrontos, Lambert, et al., 2025), this can be applied to complex, full-body movements like a physical therapy squat. In such a system, real-time motion capture tracks the user's posture; if deviations occur, precisely targeted and personalized EMS provides a gentle, intuitive muscular cue to guide the user back into the correct form. This creates a closed-loop system enabling autonomous, at-home training that is both effective and safe, potentially providing the immediate, personalized feedback of a human therapist in a scalable virtual environment.

8.4.4 Implications for Teleoperation and Prosthetics

For teleoperation and prosthetics, where conveying information about a remote or artificial effector is paramount, the framework offers a path toward more intuitive and embodied control. The demonstration that the dual-muscle EMS strategy (Study 1, Part A) can realistically render weight means an operator controlling a remote robotic arm could directly feel the weight and inertia of objects being manipulated. This rich

proprioceptive feedback channel, absent in most current systems, could dramatically improve dexterity, reduce cognitive load, and enhance safety in delicate or hazardous remote tasks. Similarly, for a prosthetic user, the principles of personalization are key to creating a more seamless connection. An adaptive system, informed by the predictive modeling approach (Study 1, Part B) and the user-specific factors identified (Study 2), could learn which EMS patterns applied to the user's arm most intuitively correspond to specific grip forces or object weights. This effectively creates a high-bandwidth, personalized sensory feedback loop, potentially leading to greater device acceptance and functional performance. Finally, the finding that required EMS intensity scales near-linearly with the relative weight difference, rather than absolute magnitude (Study 2), provides a crucial insight for simplifying the design of such feedback systems, suggesting that the mapping between sensed force and delivered EMS can be less complex than previously assumed.

8.5 Limitations of the Research

While the three-study progression provided a robust framework for personalized EMS-based weight feedback, it is essential to critically acknowledge the limitations inherent in its design. These limitations, define the boundaries of the present work and provide clear directions for future research.

The most significant limitation across all three empirical studies is the demographic profile of the participant samples. The research predominantly involved young university students, a group largely representing individuals within a typical BMI range and consistent with the demographic gap identified in the systematic literature review. While recruiting from this relatively homogeneous group enhanced internal validity by reducing variance, it limits the direct generalizability of the findings to a broader population. Factors such as age-related declines in proprioceptive acuity, significant differences in body composition (e.g., subcutaneous fat levels outside the range studied), or the presence of motor impairments in clinical populations could alter the perception of and response to EMS. Therefore, the specific quantitative findings and the performance of the personalization models should be considered most representative of this younger demographic, with further validation required for more diverse populations.

A second major limitation pertains to the ecological validity of the experimental tasks. To achieve a high degree of experimental control, all three studies employed quasi-static tasks that primarily involved holding a weight steady in a fixed posture. This necessary simplification does not capture the dynamic nature of real-world object manipulation,

which involves continuous movement and variable forces. The null result for the objective motor behavior (jerk) analysis in the third study may be an indicator of this; the task may have been too simple to elicit a strong reflexive response. Furthermore, the inherent joint stiffness and kinematic dampening caused by muscle co-contraction during static postures likely masked the subtle motor adjustments that might be detectable in dynamic lifting scenarios. Additionally, while rest breaks were employed, the effects of prolonged EMS and the resulting muscle fatigue—a known challenge of EMS due to its inverted recruitment pattern (Diamant & Reilly, 2011; Gregory & Bickel, 2005)—were not the focus of these relatively short trials.

Beyond task design, the scope of the haptic rendering and the personalization models was intentionally focused. The research exclusively investigated the sensation of downward force and targeted a specific synergistic muscle pair. While this focus was necessary for a systematic investigation, the framework's applicability to rendering other haptic effects—such as torque, shear forces, or inertia—is not yet established and would require stimulating different muscle synergies. Furthermore, the use of a fixed 1:1 normalized intensity ratio for the dual-muscle EMS is a simplification of the body's complex activation patterns. The implementation also relies on a manual calibration of individual thresholds [MT, PT], which involves inherent subjectivity and requires dedicated time. Similarly, the user model was focused on physiological and anthropometric data. While a fully robust model would capture user goals or cognitive styles (Germanakos & Belk, 2016; Neumayr & Augstein, 2020), this focused approach was a deliberate choice to first establish the foundational link between physical makeup and perceptual response.

Finally, a statistical limitation regarding the exploratory correlation analysis in the final study must be noted. Given the high number of correlations tested (135), the individual relationships identified between physical traits and outcomes did not survive strict multiple-comparisons correction. While these findings align with the individual variability observed in the previous studies, they remain tentative trends. This highlights the need for future large-scale studies to definitively map these physiological relationships with higher statistical power. Consequently, while the developed models serve as a preliminary proof-of-concept, they represent groundwork upon which more complex, multi-dimensional personalization solutions can be built.

8.6 Directions for Future Work

The findings and framework developed in this thesis serve as a robust foundation for the future of EMS-based haptics, while the identified limitations illuminate several promis-

ing and necessary directions for future research. This section outlines key avenues for investigation that can build directly upon the present work to deepen, broaden, and apply the established principles.

First, future work must transition from quasi-static to dynamic, closed-loop interactions. The experimental tasks in this thesis were intentionally simplified to establish foundational principles. A critical next step is to validate this framework in tasks involving dynamic object manipulation such as lifting, throwing, catching, or interacting with moving virtual objects within fully integrated systems, such as the VR demonstrator developed alongside this research (see Figure 8.1). This would not only test the framework's robustness in more ecologically valid scenarios but would also allow for a re-evaluation of objective motor behaviors. The null finding for movement jerk in Study 3, for example, could be revisited in a dynamic lifting task within such a VR setup, where sensory conflicts are more likely to manifest as measurable, reflexive motor corrections.

Second, the generalizability of the framework must be tested across diverse populations. The participant samples in this research were largely composed of young, healthy individuals. Future studies should intentionally test the robustness of the framework and the predictive accuracy of the personalization models on a wider range of participants, particularly older adults and individuals from clinical populations (e.g., stroke survivors, individuals with motor impairments). This research is essential for adapting the personalization models to the unique physiological and perceptual needs of key target groups for whom rehabilitative and assistive applications hold the most promise.

A third promising direction is to expand the expressive range of EMS-based haptics. This thesis focused exclusively on rendering the sensation of downward force to simulate weight. The core principles of synergistic muscle actuation and personalization should be applied to the rendering of more complex haptic effects, such as the rotational force of torque, the resistive sensation of shear forces, or the sharp "kick" of an impact. This would require stimulating more complex muscle synergies, potentially including the shoulder and back, and represents a significant step toward creating richer, more physically convincing, and ultimately full-body haptic experiences.

Furthermore, the ML models for personalization should be significantly advanced. The proof-of-concept models developed in this work can be enhanced by moving toward a truly adaptive, closed-loop system. Future iterations should be trained on larger, more diverse datasets and incorporate real-time physiological data, such as EMG, as input features. This would enable an online learning system that responds not just to a user's static profile, but to their real-time muscle fatigue and effort during a single session, creating a haptic experience that is continuously and dynamically optimized.

Finally, beyond improving the technology itself, a significant avenue for future research



(a) (b)

Figure 8.1: The VR demonstrator system integrating EMS-augmented weight perception: (a) User interacting with the system, wearing a Meta Quest 3 headset and EMS electrodes. (b) Corresponding first-person view within the virtual physiotherapy environment showing interactive dumbbells. Reprinted from Vrontos, Zolnouri, Mertens, et al. (2025), licensed under CC BY 4.0.

lies in developing and validating pedagogical frameworks for its effective application in skill acquisition within immersive digital environments like Extended Reality (XR)—a term encompassing Virtual, Augmented, and Mixed Reality. As explored in a related project (Vrontos, Lambert, et al., 2025), the findings of this thesis can be integrated into structured teaching and learning concepts for XR-based movement training. This involves designing curricula that leverage established educational models, such as Peyton's four-step approach, to guide users through complex motor tasks in a virtual environment. Future work should focus on formally evaluating the efficacy of such integrated haptic-pedagogical systems, moving beyond user experience to measure concrete learning outcomes, skill retention, and the effective transfer of motor skills from the virtual to the real world.

9 Conclusion

This thesis was motivated by a critical gap in the field of haptics: the lack of a systematic, evidence-based framework for rendering realistic and personalized weight sensations using EMS. Through a multi-study investigation, this research has systematically addressed this gap, providing a clear pathway from foundational principles to integrated, multisensory application.

9.1 Summary of Contributions

The primary scientific contribution of this thesis is the development and validation of a comprehensive, multi-tiered framework for rendering realistic and personalized weight sensations using EMS (O5). This framework is built upon the findings of a systematic literature review and three interconnected empirical investigations that sequentially and systematically addressed key gaps in the field.

The main contributions are as follows:

1. Substantiated and Defined the Critical Research Gaps: The systematic literature review provided the foundational contribution by identifying a promising but fragmented field. It highlighted a pervasive lack of methodological consensus, a reliance on homogeneous participant samples, and an absence of systematic comparisons between different EMS strategies, thereby providing the clear, evidence-based justification for the subsequent empirical work.

2. Established a Foundational EMS Strategy (O1): Addressing the first major gap, this research provides the first systematic, quantitative evidence establishing the superiority of a synergistic, dual-muscle EMS strategy over single-muscle approaches. The findings from the first empirical study demonstrated that this technique is not only perceived as significantly more realistic but is also more efficient.

3. Demonstrated the Feasibility of Data-Driven Personalization (O2): Having established an effective EMS strategy, the research next demonstrated a viable path

toward its personalization. The development of ML models that predicted perceptual outcomes with F1-scores of up to 77% serves as a crucial proof-of-concept. The feature importance analysis confirmed that a predictive model must integrate both the applied EMS parameters and the user's unique physiological characteristics.

4. Quantified the Influence of Contextual and User-Specific Factors (O3): The second study provided the deep quantification necessary to validate and inform a personalized approach. It provided quantitative evidence that ergonomics are important for perceived realism, with neutral holding postures being rated highest, and identified a perceptual optimum for weight augmentation. Critically, by identifying clear trends where individual user characteristics (e.g., age, BMI, strength) are associated with perceptual outcomes, this study motivates the adaptive ML approach demonstrated in the first study.

5. Defined the Principles of Multisensory Integration (O4): Finally, this work situated the personalized and quantified EMS strategy within the broader context of immersive experiences. The findings from the third study confirmed that visuohaptic congruence is essential for maximizing perceived realism and presence, while incongruent stimuli create a perceptual dissonance that can break immersion.

In synthesis, these contributions provide a cohesive, evidence-based pathway for designing effective EMS-based haptics, guiding developers from the initial identification of research gaps through to final integration in a multisensory virtual environment.

9.2 Concluding Remarks

The research presented in this thesis marks a significant step in the maturation of EMS-based haptics, moving the field from isolated proof-of-concept demonstrations toward a more principled and systematic methodology for design. The journey—from establishing a foundational EMS strategy, to demonstrating its potential for data-driven personalization, to quantifying the ergonomic and contextual factors that modulate its effectiveness, and finally to integrating it within a complete multisensory context—illustrates a clear trajectory for the field: a move away from static, "one-size-fits-all" systems toward intelligent, adaptive interfaces that respond to the user.

While this work focused specifically on the sensation of weight, the underlying principles of synergistic muscle actuation, ergonomic consideration, data-driven personalization, and visuohaptic congruence provide a robust template for the development of a

much wider vocabulary of haptic effects. The ultimate potential of this research lies in its ability to bridge the gap between the digital and the physical, enabling applications where the sense of weight is not merely an add-on, but a fundamental and realistic component of the experience. This could manifest as a surgeon feeling the subtle resistance of tissue in a virtual trainer, a stroke patient receiving precisely dosed and motivating resistance during remote physiotherapy, or a teleoperator intuitively sensing the forces acting on a remote robotic arm in a hazardous environment.

By placing the individual user at the center of the haptic design process, this work contributes to a future in which virtual interactions are not just seen and heard, but are truly felt.

Appendix

A. Supplementary Material for Literature Review

Table A.1: Summary of the extracted information from the identified literature. Reprinted from Vrontos et al. (2024), licensed under CC BY 4.0.

Paper	Research question/problem	Body part	Experimental setup	Stimulation parameters*	Study	Results
Kruijff et al. (2006)	Pioneering research in using EMS for force-related haptic feedback	Biceps or brachioradialis muscle	3D environment Quake3; Laptop; Stimulator Schwamedico SM;	Form: rect. biph. I: 10-25 mA V: - PW: - F: 3-5 Hz EL: -	Sample: n=7 (1 female); Age: - Scope: examined EMS intensity for muscle contraction and how to replicate the feeling of being hit by an object Measures: 5-level Likert about overall experience	Higher fat level and bigger arm required a higher stimulation intensity to activate the muscle; "Pain" and "reaction loss" were rated rather positively; The findings about "feedback", "excitement" and "further usage" were split
Farbiz et al. (2007)	Developed EMS-based haptic system for tennis in mixed reality	Forearm	Head mounted display, marker tracking, microcontroller, PC with physics simulation	Form: - I: - V: - PW: - F: - EL: 2	Sample: - Age: - Scope: - Measures: -	-

*Rect.=Rectangular, mono.=monophasic, biph.=biphasic, rect.=rectangular, PW=Pulse width, PD=Pulse duration, I=current amplitude, F=Frequency, V=Voltage, EL=electrodes, - =not mentioned in the paper

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Table A.1: Continued

Paper	Research question/problem	Body part	Experimental setup	Stimulation parameters*	Study	Results
Lopes and Baudisch (2013)	Developed a portable EMS system that can hide behind a smartphone device and produce force feedback while playing a game	Flexor carpi radialis, flexor digitorium superficialis	Stimulator consists of Arduino Uno and amplifier; smartphone HTC One X; Four reed relays; digital spring-scale to measure force	Form: biph. I: from visible contraction to pain limit V: - PW: 290 μs F: 25 Hz EL: 4 x pregelled	Sample: 1) n=10 (2 female); 2) n=10 (3 female); Age: 1) M=31.2, SD=9; 2) M=27.4, SD=5.4; Scope: 1) Measure the force from EMS-induced palm flexion; 2) compared EMS with vibrotactile feedback Measures: 5-level Likert	Study 1: Highest generated force 18.7 N for a pulse duration of 1000 ms; Study 2: EMS feedback more enjoyable than vibrotactile feedback (Mdn=4.5/5); EMS feedback reportedly leads to more positive experience (Mdn=4.5/5)
Pfeiffer et al. (2013)	Demonstrated the use of EMS for haptic feedback in public spaces	Both lower-arms	Microsoft Kinect, custom EMS-system: Arduino, control unit, battery	Form: - I: - V: - PW: 260 μs F: 50-70 Hz EL: 4	Sample: - Age: - Scope: - Measures: -	-
Lopes, Ion, et al. (2015)	Used EMS on the lower-arm for eyes-free interaction	Extensor digitorum, flexor digitorum superficialis	3d-printed bracelet, EMS-system: TruTens V3, amplifier X9C103 10Kohm, Arduino Nano & Bluetooth, EMG: AD8221 differential amplifier, Accelerometer: WAX3/WAX9	Form: Biphasic I: Up to 100 mA V: - PW: 150 μs F: 120 Hz EL: 4 (50x50mm)	Sample: 1) 10 participants (3 female), 2) 12 participants (3 female) Age: - Scope: verify interaction concept, investigate emotional response Measures: Goniometer for angle measurement	Wrist poses recreated by the participants with an average error of 5.8°, all participants reported the feeling of "fun" when playing a custom game
Lopes, Jonell, and Baudisch (2015)	EMS-based system that allows objects to communicate their use (motion, sequence of movements, time-varying behaviors) to the user	Flexor digitorum, flexor carpi radialis, extensor digitorum, flexor digitorum profundus, biceps brachii	EMS-System (4-channel): X9C102 digital potentiometer, microcontroller (ATMEGA328); 8-camera Optical tracking system: Optitrack, RFID sensor: SM130 Mifare 10MHz	Form: - I: Up to 100 mA V: - PW: 150-250 μs F: 80-140 Hz EL: up to 4	Sample: 12 participants (2 female, 10 male) Age: M=25, SD=3.36 Scope: Evaluate the effectiveness of EMS in conveying the affordance of an object Measures: 7-item Likert scales, questionnaires focusing on the identification of the intended affordance	76% of participants correctly identified the behaviors the object had been intended to communicate and all participants figured out how to use the object

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Table A.1: Continued

Paper	Research question/problem	Body part	Experimental setup	Stimulation parameters*	Study	Results
Kurita et al. (2016)	Calculated a mathematical model that allows rendering the stiffness of objects as torque at the user's elbow joint as a function of the applied voltage on the biceps muscle	Biceps muscle	HMD as visual display system ; and EMS system; PC with Unity engine and LabView; ARtoolKit for optical motion tracking; Stimulator ULI-100, Unique Medical Co., Ltd.; D/A converter NI USB-6215; Phantom premium (Sensable Inc.); Force transducer sensor	Form: Mono. rect. I: - V: 0-100 V PW: 0.4 ms F: 50 Hz EL: 2 rectangular	Sample: n=4 (all male) Age: 22-24 y.o. Scope: The participants pushed with their arm on a haptic device, until the perceived stiffness matched with the EMS-evoked stiffness Measures: Measured force that was generated by stimulation of biceps muscle using a force transducer sensor	Estimated exerted force and measured exerted force: $R^2 > 0.97$, $p < 0.001$; Target stiffness and perceived stiffness: $R^2 = 0.896$, $p < 0.001$; Maximal stiffness achieved ca. 0.3 N/mm by around 65 V
Lopes et al. (2017)	Used the system developed in (Lopes et al., 2018) for rendering haptics of heavy objects and "repulsion forces" in VR applications	extensor digitorum, extensor carpis ulnaris, biceps, triceps, infraspinatus, teres major/minor	Stimulator Rehastim, Hasomed, Germany; PC with Unity3D; Optical trackers 8 x Optitrack's Prime 17W;	Form: - I: 15-20 mA V: - PW: 70-200 μs F: - EL: 8 electrodes	Sample: 1) n=13 (4 female); 2) n=6 (1 female); Age: 1) M=22.4, SD=2.1; 2) M=22, SD=2.09; Scope: 1) Realism, consistency, and user-preference of different wall-penetrating methods; 2) Experience of using EMS feedback versus no feedback; Measures: Likert scale	EMS-rendered soft objects were more believable than hard ones, and repulsion method had the least wall penetration. Most participants preferred EMS over vibrotactile feedback, and it also increased user enjoyment and realism, particularly when combined with electro visuals
Harris et al. (2016)	Approach that uses EMS-based feedback to evoke the haptic effect of "hitting" a virtual wall	Triceps brachii muscle, Biceps brachii muscle	Torque-Force sensor Futek; 1-DOF elbow platform; Stimulator RehaStim from Hasomed; Potentiometer Midori Green Pot; PC; Quanser Q8-USB and QuaRC; Mathworks Matlab Simulink; Oscilloscope Rigol	Form: biph. rect. I: 0-80 mA V: - PW: First trials 25, 35 and 45 μs second trials 0-300 μs F: - EL: hydrogel adhesive	Sample: n=2 Age: - Scope: Four scenarios are tested: pre-wall at 9°, no pre-wall or antagonist stimulation, antagonist stimulation (biceps) with pre-wall, antagonist stimulation (biceps) no pre-wall Measures: Potentiometer for angle measurement	The scenarios with the pre-wall performed best, while antagonist stimulation also reduced the oscillations and led to a more realistic result

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Table A.1: Continued

Paper	Research question/problem	Body part	Experimental setup	Stimulation parameters*	Study	Results
Ebisu et al. (2017)	EMS-based system for learning music intstruments	Extensor carpi radialis longus and brevis, brachioradial, gastrcnemius	Arduino, PC, DC power source, electrode pads	Form: - I: - V: 17-29 V PW: 800 μs F: 50-70 Hz EL: OMRON HV-LLPAD	Sample: 12 participants (2 female) Age: M=20, SD=2.07 Scope: Evaluate the use of EMS for rhythm learning and helping users play musical instruments Measures: Interviews and position of hand	50% of participants was able to produce the correct rhythm when using the system
Lopes et al. (2018)	Developed a mobile EMS system for providing EMS-based force feedback in AR/VR applications	Teres major, Triceps, Biceps, Supinator, Pronator teres, Extensor digitorum, Flexor carpi radialis	EMS system RehaStim2, Windows-based laptop and Microsoft HoloLens	Form: - I: 15-27 mA V: - PW: 100-420 μs F: - EL: 10 electrodes	Sample: n=12 (2 female) Age: M=22.7, SD=4.9 Scope: The hypothesis of the study was that EMS-based feedback by the execution of specific applications would lead to higher realism and enjoyment of the users against no EMS feedback Measures: The realism and enjoyment were reported using a seven-level Likert scale	EMS system led to significantly more realism. And for two out of three applications the enjoyment was significantly higher using EMS-haptic feedback.
Khamis et al. (2019)	Developed an EMS-based system to elicit physical sensations to different body parts while viewing animation cutscenes in VR games	Deltoid muscle, Biceps, Flexor digitorum superficialis, Extensor digitorum	EMS generator toolkit by (Pfeiffer et al., 2016), EMS control module STIM-PRO X9+, PC with i7 6500k processor, HTC Vive headset with controller, Unity VR	Form: - I: - V: 0-50 V PW: 100 μs F: 100 Hz EL: 8 pads 5x5cm; 4 pads 10x5cm	Sample: n=22 (14 females) Age: M=24, SD=3 Scope: Test if the approach leads to more realism and presence of cutscenes in VR animations (conditions: no feedback, vibrotactile feedback, and EMS feedback) Measures: Results rated using IPQ, seven-level Likert questionnaire and interview	EMS-based feedback outperformed no feedback or vibrotactile feedback on the perceived realism, presence, involvement and sense of being there
Pfeiffer et al. (2019)	Used EMS in a virtual environment for training employees to remember workflows	Extensor digitorum; Flexor digitorum profundus;	EMS generator toolkit by (Pfeiffer et al., 2016); EMS control module STIM-PRO X9+; Laptop with Unity3D; HTC Vive controller; HMD SteamVR;	-	Sample: n=8 (2 female) Age: 18-28 y.o. Scope: Test four conditions: i) no haptic feedback, ii) prevent pushing incorrect buttons, iii) encourage pushing correct buttons, iv) last two combined; Measures: Duration and success rate for a sequence are recorded; 5-level Likert about EMS comfort	The EMS-based feedback was not perceived as uncomfortable and reportedly most of the participants felt that it supported them

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Table A.1: Continued

Paper	Research question/problem	Body part	Experimental setup	Stimulation parameters*	Study	Results
J. Lee et al. (2020)	Presented a mathematical force response model for the forearm extensor muscles that can be used for applications in haptics	Forearm extensor muscles (extensor digitorum, extensor carpi radialis longus, extensor carpi ulnaris, extensor digiti minimi)	Computer; EMS system RehaMove3, Hasomed, Germany; DAQ board NI USB 6008, National Instruments, USA; amplifier; torque sensor NT-200KC, Sensor solution, Korea	Form: biph. rect. I: specified during calibration phase according to the motor threshold and pain limit V: - PW: 400 μs F: 20, 30 or 40 Hz EL: 5x5cm, Valutrode, Denmark	Sample: n=10 (1 female) Age: M=26.4 , SD=1.96 Scope: Compare experimental and estimated peak force (NRMSE, R^2) in order to prove the validity of presenting the force as an exponential function; Compare experimental and simulated force response in order to prove the validity of the mathematical model Measures: -	Accuracy of estimated peak force: R^2 >0.96, NRMSE< 9% Accuracy of force response model: $0.82 < R^2 < 0.93$, $8.06\% < NRMSE < 13.1\%$
Ishimaru and Saga (2020)	Developed a haptic display that emulates hitting bumps with the finger	Near extensor digitorum muscle (exact location is found empirically)	Custom developed stimulator device; PC with touchscreen; Force sensor RS PRO 5000 g	Form: - I: - V: - PW: 0.5 ms F: 60 Hz EL: 2 x single-use 50x35mm	Sample: n=11 (all male) Age: 21-23 y.o. Scope: 1) Compare the EMS-based approach to other approaches; 2) Compare different EMS-based virtual bumps with real bumps; 3) Examine the wavelength property of the EMS-based virtual bumps Measures: force gauge for force measurement, questionnaire	The EMS-based approach can substitute the vibro-based approach for virtual bumps with an amplitude greater than 3 mm
Faltaous et al. (2022)	Investigated which muscles create believable haptic feedback that emulates the weight of virtual objects	Flexor carpi ulnaris, brachioradialis, biceps brachii, triceps brachii	OptiTrack 13W optical tracking system, EMS-system: Let-Your-Body-Move, EMS signal generators: Beurer Sanitas SEM 43 Digital EMS/TENS	Form: - I: - V: - PW: - F: - EL: -	Sample: n=10 (3 female) Age: MD = 29.5, SD = 12.5 Scope: How stimulating four different muscles affects the perceived weight sensation Measures: Self-reported feedback (7-point Likert scale) for the perceived weight, intensity, and comfort	Biceps brachii and triceps brachii increase the perceived weight, biceps brachii has the highest actuation intensity, brachioradialis provides the most comfortable actuation

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Table A.1: Continued

Paper	Research question/problem	Body part	Experimental setup	Stimulation parameters*	Study	Results
Galofaro et al. (2022)	Experimental setup designed to augment the interaction with VR objects by generating a haptic sensation of weight in the antagonist muscles	Biceps/triceps	Teslasuit; Oculus Rift S; Unity 3D; ergospirometer Cosmed K5; IMUs; force sensor FUTEK, FSH04416; acquisition board Quanser QPIDe	Form: - I: Up to 150 mA V: Up to 60 V PW: 1-60 μs F: 60 Hz EL: -	Sample: n=12 (10 female) Age: MD = 27.4, SD = 3.8 Scope: Track the arm movement of a VR avatar while holding a virtual cube under three conditions: i) physical feedback, ii) EMS feedback, iii) visual feedback Measures: IMUs for angle measurement, force sensor for force measurement, 7-point Likert scale for pleasantness and naturalness	NMES does not interfere with the range of motion, but affects the smoothness of the natural movement; NMES feedback was perceived as "slightly uncomfortable", but significantly more natural than only visual feedback

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B. EMS Haptics Reporting Protocol

Table B.1: EMS Haptics Reporting Protocol. *Asterisk (*) denotes context-dependent parameters.

Category	Parameters to Report (with examples)
Participant	Sample details: Age, Sex, BMI. Handedness* (e.g., Edinburgh Inventory). Other Demographics* (e.g., fitness, VR experience).
Hard- & Software	Device: Manufacturer, Model (e.g., HASOMED© P24), # Channels. Software: Control Platform (e.g., Python), Custom or COTS.
Electrodes	Details: Mfr, Material (e.g., hydrogel), Type (e.g., self-adhesive). Size(s): Dimensions (e.g., 10x5 cm, 5x5 cm). Skin Prep: Preparation (e.g., alcohol wipe, shave). Number per channel: (e.g., 2), Lifespan/Usage*.
Placement	Target Muscle(s): Names (e.g., Triceps Brachii). Arm: Stimulated arm (e.g., Dominant). Guidance: Motor point location method (e.g., charts Behringer et al. (2014)).
EMS Parameters	Waveform: Pulse shape (e.g., Symmetrical biphasic rect.). Frequency: Fixed value (e.g., 40 Hz). Pulse Width: Fixed value (e.g., 120 μs). Modulation: Parameter varied for intensity (e.g., Current Amplitude). Ramp Time*: Onset/offset duration (e.g., 200 ms).
Calibration	Protocol: Threshold finding method (e.g., Step-wise). Definitions: Clear definitions for ST (tingle), MT (twitch), PT (pain onset). Scaling: Intensity normalization (e.g., % of [MT, PT] range). Recalibration*: (e.g., per session).
Task & Setup	Task: Primary task (e.g., Static hold, lift). Posture: Required posture (e.g., 90-degree elbow). Apparatus: Key equipment (e.g., HMD, object). Data Logged*: Variables recorded.
Ethical Considerations	Informed Consent: Confirm written consent obtained. Ethics Approval: Institution and approval number. Health Exclusions: Exclusion criteria (e.g., pacemakers). Safety Protocol: Measures (e.g., user stop, cut-offs).
Other Factors	Fatigue Management*: (e.g., rest periods). Blinding*: Blinding procedure (e.g., single-blind).

C. Python Code for EMS Device Control

This appendix provides the core Python code used for low-level communication and control of the HASOMED© P24 EMS device during the empirical studies. It includes functions for establishing USB connection, formatting commands according to the device protocol (including checksum calculation), and generating specific EMS patterns like biphasic pulses and amplitude sequences used in the experiments. Note that this code requires the 'pyusb' library and appropriate USB drivers.

For the 'pyusb' library to communicate with the HASOMED© P24 device on Windows, a compatible USB driver must be installed to replace the default serial port driver. This typically involves using a tool like the installer provided with the 'libusbK' development kit. After connecting the P24 device, the 'libusbK' installer (specifically, the 'InfWizard' tool included with it) should be run. During the installation, select the 'libusbK' kernel driver package. Then, identify the connected HASOMED© device (Vendor ID 0x0483, Product ID 0x5740, often listed as "STM32 Virtual ComPort") from the list of all USB devices and install the 'libusbK' driver specifically for it. An additional step involves installing the 'libusb-win32 filter driver' for the same device to allow communication via the libusb API while maintaining compatibility. After completing these steps and rebooting the system, Windows Device Manager should show the device using the 'libusbK' driver instead of the default 'usbser.sys', enabling communication via the Python script.

```
# -*- coding: utf-8 -*-
"""
Core Python script for low-level communication and control of the
HASOMED P24 EMS device via USB. Includes functions for connection,
protocol-specific command framing (checksum, length, escaping),
and generating EMS patterns. Requires pyusb library and
correctly installed libusbK drivers.
"""

import usb.core
import usb.util
import time
import numpy as np
import random
from IPython.display import clear_output

def setup_usb():
    device = usb.core.find(idVendor=0x0483, idProduct=0x5740)
    if device is None:
```

```
20          raise ValueError("Device not found")
21      device.set_configuration()
22      interface = 1
23      usb.util.claim_interface(device, interface)
24
25      out_endpoint = None
26      in_endpoint = None
27      for cfg in device:
28          for intf in cfg:
29              for ep in intf:
30                  if usb.util.endpoint_direction(ep.bEndpointAddress) ==
    usb.util.ENDPOINT_OUT:
31                      out_endpoint = ep
32                  elif usb.util.endpoint_direction(ep.bEndpointAddress)
    == usb.util.ENDPOINT_IN:
33                      in_endpoint = ep
34
35      if out_endpoint is None or in_endpoint is None:
36          raise ValueError("Both OUT and IN endpoints are required for
    communication.")
37
38      return device, out_endpoint, in_endpoint
39
40  def send(data, device, out_endpoint):
41      device.write(out_endpoint.bEndpointAddress, data)
42
43  def HtB(hex_string):
44      hex_values = hex_string.split()
45      binary_values = []
46      for hex_value in hex_values:
47          decimal_value = int(hex_value, 16)
48          binary_value = bin(decimal_value)[2:].zfill(8)
49          binary_values.append(binary_value)
50      return binary_values
51
52  def BtH(binary_string):
53      binary_values = binary_string.split()
54      hex_values = []
55      for binary_value in binary_values:
56          decimal_value = int(binary_value, 2)
57          hex_value = hex(decimal_value)[2:].upper().zfill(2)
58          hex_values.append(hex_value)
59      return hex_values
60
```

```
def list_glue(string_list):
    s=""
    for i in string_list:
        s+=i
    return s

def hex_xor(hex1, hex2):
    int1 = int(hex1, 16)
    int2 = int(hex2, 16)
    xor_result = int1 ^ int2
    hex_result=format(xor_result, '02X')
    return hex_result

def checksum(hex_sequence):
    crc = 0x0000
    hex_values = hex_sequence.split()
    for hex_value in hex_values:
        data = int(hex_value, 16)
        crc ^= data << 8
        for _ in range(8):
            if crc & 0x8000:
                crc = (crc << 1) ^ 0x1021
            else:
                crc <<= 1
    crc &= 0xFFFF
    crcmodem = format(crc, '04X')
    crc0 = format(crc, '04X')
    return "81" + " " + hex_xor(crc0[:2],'55') + " " + "81" + " " +
   hex_xor(crc0[2:],'55')

def length_cal(command_str):
    l = 10 + len(command_str.split())
    l = hex(l)[2:]
    l = hex_xor(l,'55')
    return "81" + " " + "55" + " "  + "81"+ " "  + l

def message_gen(data_string):
    m = "F0" + " " + length_cal(data_string)+ " " + checksum(
   data_string) + " " + data_string + " " + "0F"
    return m

def init():
    command= "00 1E 00"
    send(bytes.fromhex(message_gen(command)), device, out_endpoint)
```

```
103
104 def stop():
105     command= "0C 22"
106     send(bytes.fromhex(message_gen(command)), device, out_endpoint)
107
108 def get_current_data(): #requests the live data and keep alive signal
109     message = message_gen("08 24 02")
110     return bytes.fromhex(message)
111
112 def split_string(string, block_size):
113     string = ''.join(string.split())
114     num_blocks = len(string) // block_size
115     blocks = [string[i:i+block_size] for i in range(0, len(string),
    block_size)]
116     out = ' '.join(blocks)
117     return out
118
119 def send_message(pw, amp, frequency, timer):
120     message1=update_1point(pw, amp, frequency)
121     message2=get_current_data()
122     init()
123     for _ in range(timer*10):
124         send(message1, device, out_endpoint)
125         send(message2, device, out_endpoint)
126         time.sleep(0.1)
127     stop()
128
129 def update_2point(amp1, amp2): #biphasic signal for two channels
130     pw = 120
131     frequency = 40
132     p1= bin(pw)[2:].zfill(12) + bin(int(2*amp1)+300)[2:].zfill(10) + "0
    "*10
133     p2= bin(pw)[2:].zfill(12) + bin(int(2*(-amp1))+300)[2:].zfill(10) +
     "0"*10
134     p3= bin(pw)[2:].zfill(12) + bin(int(2*amp2)+300)[2:].zfill(10) + "0
    "*10
135     p4= bin(pw)[2:].zfill(12) + bin(int(2*(-amp2))+300)[2:].zfill(10) +
     "0"*10
136     ramp = 3
137     block_1_8 = "00000011" # Channel - Yellow output, Blue wire: amp2,
    Red wire: amp1
138     block_2_8 = bin(1)[2:].zfill(4) + bin(ramp)[2:].zfill(4) # number
    of points = 2
139     block_3_16 = bin(((1000*2)//frequency))[2:].zfill(15) + "0"
```

```
140     command_block= "04 20" + " " + split_string(list_glue(BtH(
        split_string(block_1_8 + block_2_8 + block_3_16 + p1 + p2 +
        block_2_8 + block_3_16 + p3 + p4, 8))), 2)
141     CB=command_block.split()
142     for i in range(len(CB)):
143         if CB[i] in ["0F","F0","81","55","0f","f0"]:
144             CB[i]="81" + " " + hex_xor(CB[i], '55')
145     CB2=''
146     for i in CB:
147         CB2 = CB2 + i
148     command_block=split_string(''.join(CB2.split()), 2)
149     ml_message = "F0" +" " + length_cal(command_block) + " " + checksum
        (command_block) + " " + command_block + " " + "0F"
150     return bytes.fromhex(ml_message)
151
152 def send_message2(amp1, amp2, timer):
153     try:
154         message1=update_2point(amp1,amp2)
155         message2=get_current_data()
156         init()
157         start_time = time.time()
158         for _ in range(timer):
159             send(message1, device, out_endpoint)
160             send(message2, device, out_endpoint)
161             time.sleep(1)
162         end_time = time.time()
163         duration_ms = (end_time - start_time)*1000
164         print("The procedure took {:.2f} milliseconds.".format(
        duration_ms))
165         stop()
166     except:
167         print("Warning: Stopped in \"send_message2()\"")
168
169 def list_message2(amp_list1, amp_list2, dt): # use multipliers of 0.05
    seconds
170     try:
171         message2 = get_current_data()
172         update_list=[]
173
174         for k in range(len(amp_list1)):
175             i = amp_list1[k]
176             j =  amp_list2[k]
177             message1=update_2point(i, j)
178             update_list.append(message1)
```

```
179         init()
180         l=-1
181         if dt<1:
182                 for s in update_list:
183                     l+=1
184                     send(s, device, out_endpoint)
185                     clear_output(wait=True)
186                     print("R:", amp_list1[l])
187                     print("B:", amp_list2[l])
188                     send(message2, device, out_endpoint)
189                     time.sleep(dt)
190         else:
191             for r in update_list:
192                 start_time = time.time()
193                 l+=1
194                 clear_output(wait=True)
195                 print("R:",amp_list1[l])
196                 print("B:",amp_list2[l])
197
198
199
200                 for t in range(int(dt)):
201                     send(r, device, out_endpoint)
202                     send(message2, device, out_endpoint)
203                     time.sleep(1)
204                 end_time = time.time()
205                 duration_ms = (end_time - start_time)*1000
206                 print("The procedure took {:.2f} milliseconds.".format(
    duration_ms)," (list_message2)")
207         stop()
208     except:
209         print("Warning: Stopped in \"list_message2()\"")
210
211 def rand_amp_gen2(low_triceps, high_triceps, low_lower_arm,
    high_lower_arm, number_of_points, seed):
212     random.seed(seed)
213     amp_list1 = []
214     amp_list2 = []
215
216     # Calculate the step size for linear incrementation
217     step_triceps = (high_triceps - low_triceps) / (number_of_points -
    1)
218     step_lower_arm = (high_lower_arm - low_lower_arm) / (
    number_of_points - 1)
```

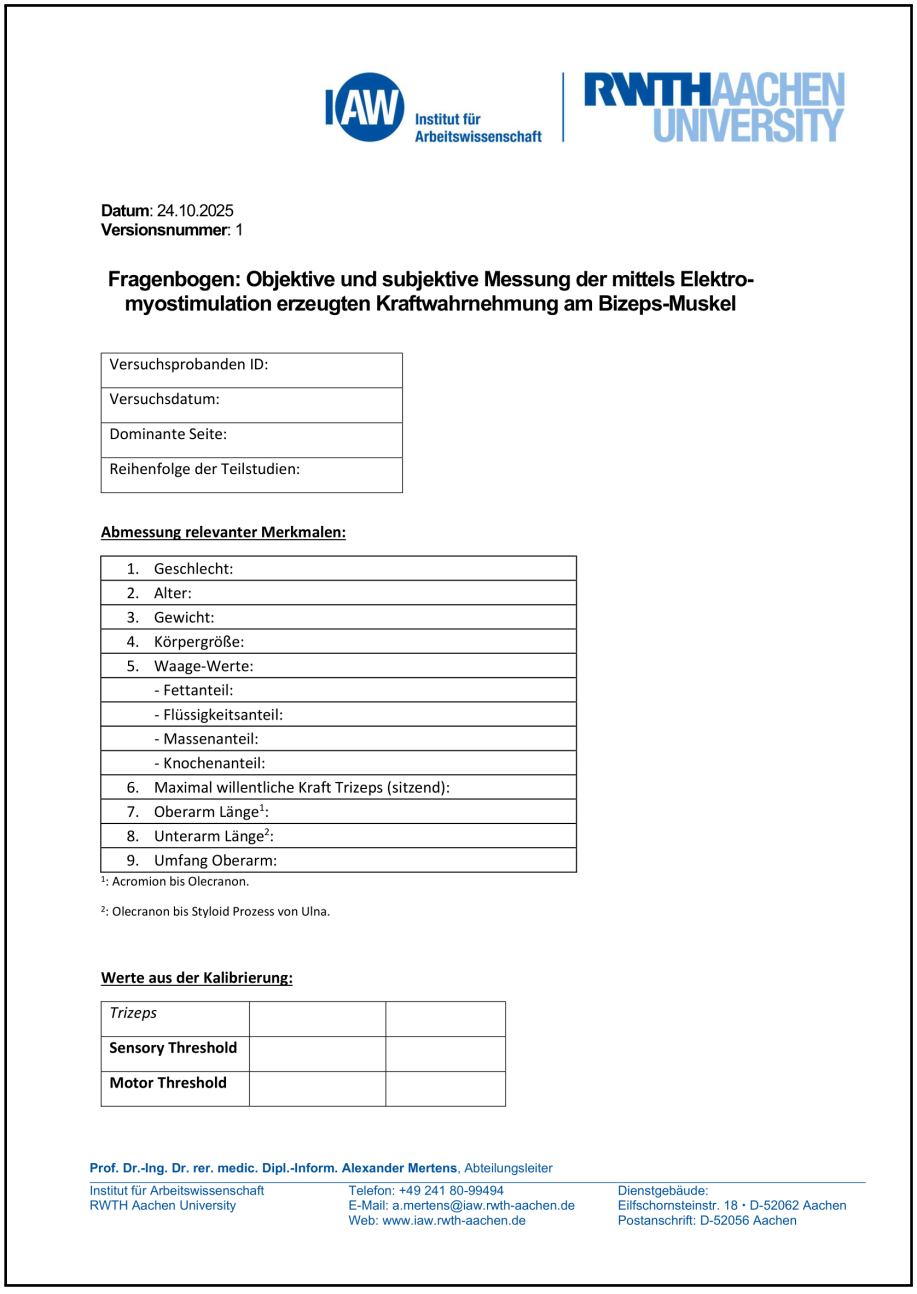
```
219
220     for i in range(number_of_points):
221         # Linearly increment the amplitude value
222         a = low_triceps + i * step_triceps
223         b = low_lower_arm + i * step_lower_arm
224
225         # Round to the nearest 0.5 and append to the lists
226         amp_list1.append(round(a * 2) / 2)
227         amp_list2.append(round(b * 2) / 2)
228
229     # Shuffle the indices
230     idx_shuffled = list(range(number_of_points))
231     random.shuffle(idx_shuffled)
232
233     # Apply the same shuffled indices to both lists
234     shuffled_amp_list1 = [amp_list1[i] for i in idx_shuffled]
235     shuffled_amp_list2 = [amp_list2[i] for i in idx_shuffled]
236
237     print("Original amp_list1, for triceps:", amp_list1)
238     print("Original amp_list2, for lower arm:", amp_list2,"\n")
239     print("Shuffled amp_list1:", shuffled_amp_list1)
240     print("Shuffled amp_list2:", shuffled_amp_list2)
241     return shuffled_amp_list1, shuffled_amp_list2
242
243 def stair_amp_gen2(low_triceps, high_triceps, low_lower_arm,
    high_lower_arm, number_of_points):
244     amp_list1 = []
245     amp_list2 = []
246
247     # Calculate the step size for linear incrementation
248     step_triceps = (high_triceps - low_triceps) / (number_of_points -
    1)
249     step_lower_arm = (high_lower_arm - low_lower_arm) / (
    number_of_points - 1)
250
251     for i in range(number_of_points):
252         # Linearly increment the amplitude value
253         a = low_triceps + i * step_triceps
254         b = low_lower_arm + i * step_lower_arm
255
256         # Round to the nearest 0.5 and append to the lists
257         amp_list1.append(round(a * 2) / 2)
258         amp_list2.append(round(b * 2) / 2)
259
```

```
260     #print("amp_list1, for triceps is", amp_list1)
261     #print("amp_list2, for lower arm is", amp_list2)
262     return amp_list1, amp_list2
263 
264 def stair_amp_gen2_with_extrapolation(low_triceps, high_triceps,
    low_lower_arm, high_lower_arm, number_of_points,
    extrapolation_percent):
265     amp_list1 = []
266     amp_list2 = []
267 
268     # Calculate the original range
269     range_triceps = high_triceps - low_triceps
270     range_lower_arm = high_lower_arm - low_lower_arm
271 
272     # Extend the high values by the extrapolation percentage
273     extrapolated_high_triceps = high_triceps + (range_triceps *
    extrapolation_percent / 100)
274     extrapolated_high_lower_arm = high_lower_arm + (range_lower_arm *
    extrapolation_percent / 100)
275 
276     # Calculate the step size for linear incrementation with
    extrapolation
277     step_triceps = (extrapolated_high_triceps - low_triceps) / (
    number_of_points - 1)
278     step_lower_arm = (extrapolated_high_lower_arm - low_lower_arm) / (
    number_of_points - 1)
279 
280     for i in range(number_of_points):
281         # Linearly increment the amplitude value
282         a = low_triceps + i * step_triceps
283         b = low_lower_arm + i * step_lower_arm
284 
285         # Round to the nearest 0.5 and append to the lists
286         amp_list1.append(round(a * 2) / 2)
287         amp_list2.append(round(b * 2) / 2)
288 
289     return amp_list1, amp_list2
290 
291 def lin_amp_gen2(speed, number_of_points):
292     amp_list1 = []
293     amp_list2 = []
294 
295     # Initial amplitude values, could be set to 0 or any starting value
296     current_amp_triceps = 0
```

```
297     current_amp_lower_arm = 0
298 
299     for i in range(number_of_points):
300         # Increase the amplitude by speed
301         current_amp_triceps += speed
302         current_amp_lower_arm += speed
303 
304         # Round to the nearest 0.5 and append to the lists
305         amp_list1.append(round(current_amp_triceps * 2) / 2)
306         amp_list2.append(round(current_amp_lower_arm * 2) / 2)
307 
308     return amp_list1, amp_list2
309 
310 # Assign handles to global variables for use in functions
311 device, out_endpoint, _ = setup_usb()  # Assuming the IN endpoint is
    not needed
```

Listing 1: Core Python script for HASOMED© P24 EMS device control via USB.

D.1 Questionnaire for Experiment 1



Institut für Arbeitswissenschaft | RWTH AACHEN UNIVERSITY

Datum: 24.10.2025
Versionsnummer: 1

Fragenbogen: Objektive und subjektive Messung der mittels Elektromyostimulation erzeugten Kraftwahrnehmung am Bizeps-Muskel

Versuchsprobanden ID:
Versuchsdatum:
Dominante Seite:
Reihenfolge der Teilstudien:

Abmessung relevanter Merkmalen:

1. Geschlecht:
2. Alter:
3. Gewicht:
4. Körpergröße:
5. Waage-Werte:
- Fettanteil:
- Flüssigkeitsanteil:
- Massenanteil:
- Knochenanteil:
6. Maximal willentliche Kraft Trizeps (sitzend):
7. Oberarm Länge[1]:
8. Unterarm Länge[2]:
9. Umfang Oberarm:

[1]: Acromion bis Olecranon.

[2]: Olecranon bis Styloid Prozess von Ulna.

Werte aus der Kalibrierung:

Trizeps		
Sensory Threshold		
Motor Threshold		

Prof. Dr.-Ing. Dr. rer. medic. Dipl.-Inform. Alexander Mertens, Abteilungsleiter

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Grenze des Unwohlseins		

Lower-arm		
Sensory Threshold		
Motor Threshold		
Grenze des Unwohlseins		

Erfassung von Ergebnissen zur Teilstudie 1:

Hinweis: Im Rahmen von Teilstudie 1 werden Sie gebeten, die folgenden Aussagen zu bewerten. Die Aussagen 1a, 1b und 1c beziehen sich auf den Abschnitt der Teilstudie, in dem lediglich der Trizeps stimuliert wird. Die Aussagen 2a, 2b und 2c beziehen sich auf den Abschnitt, in dem zusätzlich der Unterarm stimuliert wird.

Aussage 1a: „Ich konnte eine Änderung in der Gewichtswahrnehmung spüren."

Stimme überhaupt nicht zu	Stimme nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme zu	Stimme voll und ganz zu
1	2	3	4	5	6	7
Kommentare:						

Aussage 1b: „Das empfundene Gewicht des Objekts hat im Laufe der Stimulation ..."

a) ... zugenommen.
b) ... abgenommen.
c) ... sich nicht verändert.

Aussage 1c (falls „zugenommen"): „Die Zunahme des empfundenen Gewichts wirkte natürlich, als ob sie durch eine reale, physische Veränderung verursacht wurde."

Stimme überhaupt nicht zu	Stimme nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme zu	Stimme voll und ganz zu
1	2	3	4	5	6	7

Kommentare:

Aussage 2a: „Ich konnte eine Änderung in der Gewichtswahrnehmung spüren."

Stimme überhaupt nicht zu	Stimme nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme zu	Stimme voll und ganz zu
1	2	3	4	5	6	7
Kommentare:						

Aussage 2b: „Das empfundene Gewicht des Objekts hat im Laufe der Stimulation ..."

a) ... zugenommen.
b) ... abgenommen.
c) ... sich nicht verändert.

Aussage 2c (falls „zugenommen"): „Die Zunahme des empfundenen Gewichts wirkte natürlich, als ob sie durch eine reale, physische Veränderung verursacht wurde."

Stimme überhaupt nicht zu	Stimme nicht zu	Stimme eher nicht zu	Weder noch	Stimme eher zu	Stimme zu	Stimme voll und ganz zu
1	2	3	4	5	6	7
Kommentare:						

Erfassung von Ergebnissen zur Teilstudie 2:

2Kg vs 3Kg	(Ohne Unterarm)	(Mit Unterarm)
Unterarm-Werte:	-	
Trizeps-Werte:		
Kommentare:		

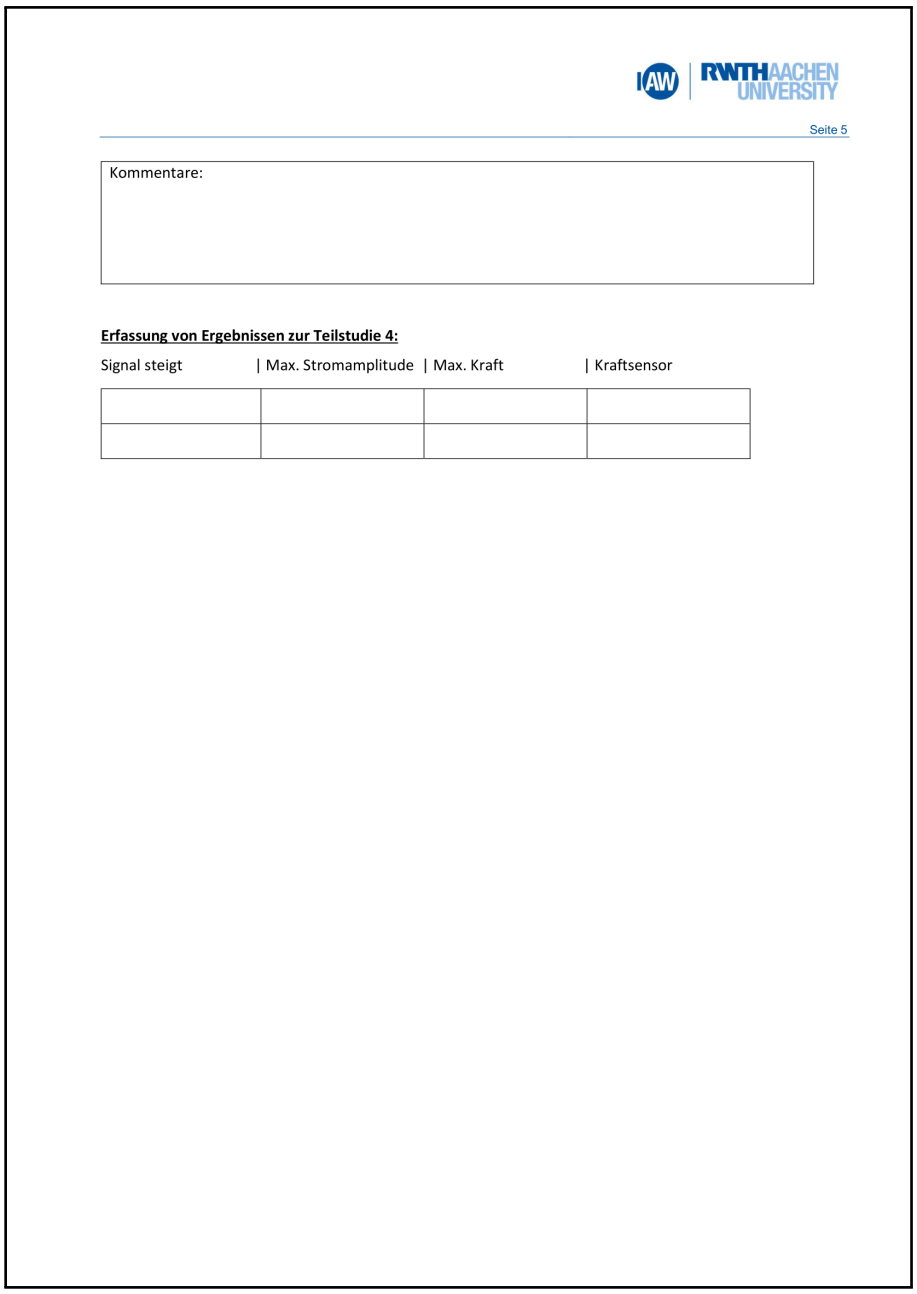
Erfassung von Ergebnissen zur Teilstudie 3:

(Ohne Unteram)

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
mA (Tr)									
Seite									
Kommentare:									

(Mit Unterarm)

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
mA (Ua)									
mA (Tr)									
Seite									



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Seite 5

Kommentare:

Erfassung von Ergebnissen zur Teilstudie 4:

Signal steigt | Max. Stromamplitude | Max. Kraft | Kraftsensor

D.2 Questionnaire for Experiment 2

Fragenbogen zur experimentellen Studie – Elektromyostimulation für Haptisches Feedback 2.0

Allgemeines		
Datum:	**Uhrzeit:**	**ID (seed):**
Demographische Daten		
Alter:	**Geschlecht:**	

Physiologische Daten						
Dominante Seite	**Größe**	**Gewicht**	**Greifkraft**	**Unterarmlänge**	**Oberarmlänge**	**Oberarmumfang**

EMS-Schwellenwerte		
Oberarm		
Sensorschwelle*	**Motorschwelle***	**Schmerzschwelle***
Unterarm		
Sensorschwelle*	**Motorschwelle***	**Schmerzschwelle***

Reihenfolge der Ellbogenwinkel	**1.**	**2.**	**3.**

1. Ellbogenwinkel										
Gewichte	**1.**	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**	**10.**
mA										
Realismus**										

2. Ellbogenwinkel										
Gewichte	**1.**	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**	**10.**
mA										
Realismus**										

3. Ellbogenwinkel										
Gewichte	**1.**	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**	**10.**
mA										
Realismus**										

***Sensorschwelle: Niedrigste Stromstärke für eine spürbare Empfindung (z.B. Kribbeln).**
***Motorschwelle: Niedrigste Stromstärke für eine sichtbare/fühlbare Muskelzuckung.**
***Schmerzschwelle: Niedrigste Stromstärke, die unangenehm oder schmerzhaft wird.**

****Realismus: „Die Zunahme des empfundenen Gewichts wirkte natürlich, als ob sie durch eine reale, physische Veränderung verursacht wurde."**

1	**2**	**3**	**4**	**5**	**6**	**7**
Stimme überhaupt nicht zu	**Stimme nicht zu**	**Stimme eher nicht zu**	**Weder noch**	**Stimme eher zu**	**Stimme zu**	**Stimme voll und ganz zu**

Kommentare:

D.3 Questionnaire for Experiment 3

Visuohaptisches Feedback Experiment: Teilnehmerfragebogen

Fortfahren, nachdem die Einverständniserklärung abgegeben wurde.

Allgemeine Daten

Datum & Uhrzeit (z.B. "31.12.2025 um 09:41 Uhr"): _____

Teilnehmer-ID (z.B. "01", "02", ..., "36"): _____

Demografische Daten

Alter (z.B. "34"): _____

Geschlecht (z.B. "m", "w"): _____

Physiologische Daten

Händigkeit (z.B. "r", "l"): _____

Körpergröße (z.B. "175 cm"): _____

Gewicht (z.B. "75 kg"): _____

Handgriffkraft (z.B. "80"): _____

Unterarmlänge (z.B. "30 cm"): _____

Oberarmlänge (z.B. "35 cm"): _____

Oberarmumfang (z.B. "35 cm"): _____

Taillenumfang (z.B. "85 cm"): _____

Hüftumfang (z.B. "100 cm"): _____

EMS Schwellenwerte

Oberarm:

- Sensorische Schwelle (z.B. "8"): _____
- Motorische Schwelle (z.B. "12"): _____
- Schmerzschwelle (z.B. "45"): _____

Unterarm:

- Sensorische Schwelle (z.B. "8"): _____
- Motorische Schwelle (z.B. "12"): _____
- Schmerzschwelle (z.B. "30"): _____

1

Trial 1 [Bedingung: _____]

A) Spezifische Einzelfragen: Ihr Erleben während des Ereignisses

Anleitung: Bitte kreisen Sie für jede der folgenden Fragen die Zahl ein, die Ihr Erleben während des soeben stattgefundenen Ereignisses am besten beschreibt.

Fragen:

1. Inwieweit haben Sie eine **Veränderung des Gewichts** der Hantel gespürt?

Keinerlei Veränderung ① ② ③ ④ ⑤ ⑥ ⑦ Eine sehr deutliche Veränderung

(Neutral)

2. Wie **realistisch** hat sich die Veränderung des Hantelgewichts angefühlt?

Überhaupt nicht realistisch ① ② ③ ④ ⑤ ⑥ ⑦ Vollkommen realistisch

(Neutral)

3. Bitte bewerten Sie das Ausmaß der **Diskrepanz** (des Auseinanderklaffens) zwischen dem, was Sie gesehen, und dem, was Sie gefühlt haben.

Keinerlei Diskrepanz ① ② ③ ④ ⑤ ⑥ ⑦ Eine sehr starke Diskrepanz

(Neutral)

4. Inwieweit hatten Sie das Gefühl, die virtuelle Hantel unter **Kontrolle** zu haben?

Überhaupt nicht unter Kontrolle ① ② ③ ④ ⑤ ⑥ ⑦ Vollkommen unter Kontrolle

(Neutral)

5. Das Objekt fühlte sich an, als ob es um ungefähr ___ **Kg** schwerer wurde (bitte eine Zahl eintragen)?

B) Igroup Presence Questionnaire (IPQ): Erleben in der virtuellen Umgebung

Anleitung: Bitte geben Sie für jede der folgenden Aussagen an, wie Sie die virtuelle Erfahrung empfunden haben. Kreuzen Sie für jede Zeile das Kästchen an, das Ihre Empfindung am besten beschreibt.

Fragen:

1. In der computererzeugten Welt hatte ich den Eindruck, dort gewesen zu sein.

überhaupt nicht ☐ ☐ ☐ ☐ ☐ ☐ ☐ sehr stark

2. Ich hatte das Gefühl, daß die virtuelle Umgebung hinter mir weitergeht.

trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

3. Ich hatte das Gefühl, nur Bilder zu sehen.

trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

4. Ich hatte nicht das Gefühl, in dem virtuellen Raum zu sein.

hatte nicht das Gefühl ☐ ☐ ☐ ☐ ☐ ☐ ☐ hatte das Gefühl

5. Ich hatte das Gefühl, in dem virtuellen Raum zu handeln statt etwas von außen zu bedienen.

trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

6. Ich fühlte mich im virtuellen Raum anwesend.

trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

7. Wie bewußt war Ihnen die reale Welt, während Sie sich durch die virtuelle Welt bewegten (z.B. Geräusche, Raumtemperatur, andere Personen etc.)?

extrem bewußt ☐ ☐ ☐ ☐ ☐ ☐ ☐ unbewußt

(mittelmäßig bewußt)

8. Meine reale Umgebung war mir nicht mehr bewußt.

trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

9. Ich achtete noch auf die reale Umgebung.

trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

10. Meine Aufmerksamkeit war von der virtuellen Welt völlig in Bann gezogen.

trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

11. Wie real erschien Ihnen die virtuelle Umgebung?

gar nicht real ☐ ☐ ☐ ☐ ☐ ☐ ☐ vollkommen real

(weder noch)

12. Wie sehr glich Ihr Erleben der virtuellen Umgebung dem Erleben einer realen Umgebung?

überhaupt nicht ☐ ☐ ☐ ☐ ☐ ☐ ☐ vollständig

(etwas)

13. Wie real erschien Ihnen die virtuelle Welt?

wie eine vorgestellte Welt ☐ ☐ ☐ ☐ ☐ ☐ ☐ nicht zu unterscheiden von der realen Welt

14. Die virtuelle Welt erschien mir wirklicher als die reale Welt.

trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

Trial 2 [Bedingung: _____]

A) Spezifische Einzelfragen: Ihr Erleben während des Ereignisses

Anleitung: Bitte kreisen Sie für jede der folgenden Fragen die Zahl ein, die Ihr Erleben während des soeben stattgefundenen Ereignisses am besten beschreibt.

Fragen:

1. Inwieweit haben Sie eine **Veränderung des Gewichts** der Hantel gespürt?

Keinerlei Veränderung ① ② ③ ④ ⑤ ⑥ ⑦ Eine sehr deutliche Veränderung

(Neutral)

2. Wie **realistisch** hat sich die Veränderung des Hantelgewichts angefühlt?

Überhaupt nicht realistisch ① ② ③ ④ ⑤ ⑥ ⑦ Vollkommen realistisch

(Neutral)

3. Bitte bewerten Sie das Ausmaß der **Diskrepanz** (des Auseinanderklaffens) zwischen dem, was Sie gesehen, und dem, was Sie gefühlt haben.

Keinerlei Diskrepanz ① ② ③ ④ ⑤ ⑥ ⑦ Eine sehr starke Diskrepanz

(Neutral)

4. Inwieweit hatten Sie das Gefühl, die virtuelle Hantel unter **Kontrolle** zu haben?

Überhaupt nicht unter Kontrolle ① ② ③ ④ ⑤ ⑥ ⑦ Vollkommen unter Kontrolle

(Neutral)

5. Das Objekt fühlte sich an, als ob es um ungefähr ___ **Kg** schwerer wurde (bitte eine Zahl eintragen)?

B) Igroup Presence Questionnaire (IPQ): Erleben in der virtuellen Umgebung

Anleitung: Bitte geben Sie für jede der folgenden Aussagen an, wie Sie die virtuelle Erfahrung empfunden haben. Kreuzen Sie für jede Zeile das Kästchen an, das Ihre Empfindung am besten beschreibt.

Fragen:

1. In der computererzeugten Welt hatte ich den Eindruck, dort gewesen zu sein.

überhaupt nicht ☐ ☐ ☐ ☐ ☐ ☐ ☐ sehr stark

2. Ich hatte das Gefühl, daß die virtuelle Umgebung hinter mir weitergeht.

trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

3. Ich hatte das Gefühl, nur Bilder zu sehen.

trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

4. Ich hatte nicht das Gefühl, in dem virtuellen Raum zu sein.
   hatte nicht das Gefühl ☐ ☐ ☐ ☐ ☐ ☐ ☐ hatte das Gefühl

5. Ich hatte das Gefühl, in dem virtuellen Raum zu handeln statt etwas von außen zu bedienen.
   trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

6. Ich fühlte mich im virtuellen Raum anwesend.
   trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

7. Wie bewußt war Ihnen die reale Welt, während Sie sich durch die virtuelle Welt bewegten (z.B. Geräusche, Raumtemperatur, andere Personen etc.)?
   extrem bewußt ☐ ☐ ☐ ☐ ☐ ☐ ☐ unbewußt

   (mittelmäßig bewußt)

8. Meine reale Umgebung war mir nicht mehr bewußt.
   trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

9. Ich achtete noch auf die reale Umgebung.
   trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

10. Meine Aufmerksamkeit war von der virtuellen Welt völlig in Bann gezogen.
    trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

11. Wie real erschien Ihnen die virtuelle Umgebung?
    gar nicht real ☐ ☐ ☐ ☐ ☐ ☐ ☐ vollkommen real

    (weder noch)

12. Wie sehr glich Ihr Erleben der virtuellen Umgebung dem Erleben einer realen Umgebung?
    überhaupt nicht ☐ ☐ ☐ ☐ ☐ ☐ ☐ vollständig

    (etwas)

13. Wie real erschien Ihnen die virtuelle Welt?
    wie eine vorgestellte Welt ☐ ☐ ☐ ☐ ☐ ☐ ☐ nicht zu unterscheiden von der realen Welt

14. Die virtuelle Welt erschien mir wirklicher als die reale Welt.
    trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

Trial 3 [Bedingung: _____]

A) Spezifische Einzelfragen: Ihr Erleben während des Ereignisses

Anleitung: Bitte kreisen Sie für jede der folgenden Fragen die Zahl ein, die Ihr Erleben während des soeben stattgefundenen Ereignisses am besten beschreibt.

Fragen:

1. Inwieweit haben Sie eine **Veränderung des Gewichts** der Hantel gespürt?
Keinerlei Veränderung ① ② ③ ④ ⑤ ⑥ ⑦ Eine sehr deutliche Veränderung

(Neutral)

2. Wie **realistisch** hat sich die Veränderung des Hantelgewichts angefühlt?
Überhaupt nicht realistisch ① ② ③ ④ ⑤ ⑥ ⑦ Vollkommen realistisch

(Neutral)

3. Bitte bewerten Sie das Ausmaß der **Diskrepanz** (des Auseinanderklaffens) zwischen dem, was Sie gesehen, und dem, was Sie gefühlt haben.
Keinerlei Diskrepanz ① ② ③ ④ ⑤ ⑥ ⑦ Eine sehr starke Diskrepanz

(Neutral)

4. Inwieweit hatten Sie das Gefühl, die virtuelle Hantel unter **Kontrolle** zu haben?
Überhaupt nicht unter Kontrolle ① ② ③ ④ ⑤ ⑥ ⑦ Vollkommen unter Kontrolle

(Neutral)

5. Das Objekt fühlte sich an, als ob es um ungefähr ___ **Kg** schwerer wurde (bitte eine Zahl eintragen)?

B) Igroup Presence Questionnaire (IPQ): Erleben in der virtuellen Umgebung

Anleitung: Bitte geben Sie für jede der folgenden Aussagen an, wie Sie die virtuelle Erfahrung empfunden haben. Kreuzen Sie für jede Zeile das Kästchen an, das Ihre Empfindung am besten beschreibt.

Fragen:

1. In der computererzeugten Welt hatte ich den Eindruck, dort gewesen zu sein.
überhaupt nicht ☐ ☐ ☐ ☐ ☐ ☐ ☐ sehr stark
2. Ich hatte das Gefühl, daß die virtuelle Umgebung hinter mir weitergeht.
trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu
3. Ich hatte das Gefühl, nur Bilder zu sehen.
trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu
4. Ich hatte nicht das Gefühl, in dem virtuellen Raum zu sein.
hatte nicht das Gefühl ☐ ☐ ☐ ☐ ☐ ☐ ☐ hatte das Gefühl

5. Ich hatte das Gefühl, in dem virtuellen Raum zu handeln statt etwas von außen zu bedienen.
   trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu
6. Ich fühlte mich im virtuellen Raum anwesend.
   trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu
7. Wie bewußt war Ihnen die reale Welt, während Sie sich durch die virtuelle Welt bewegten (z.B. Geräusche, Raumtemperatur, andere Personen etc.)?
   extrem bewußt ☐ ☐ ☐ ☐ ☐ ☐ ☐ unbewußt

   (mittelmäßig bewußt)
8. Meine reale Umgebung war mir nicht mehr bewußt.
   trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu
9. Ich achtete noch auf die reale Umgebung.
   trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu
10. Meine Aufmerksamkeit war von der virtuellen Welt völlig in Bann gezogen.
    trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu
11. Wie real erschien Ihnen die virtuelle Umgebung?
    gar nicht real ☐ ☐ ☐ ☐ ☐ ☐ ☐ vollkommen real

    (weder noch)
12. Wie sehr glich Ihr Erleben der virtuellen Umgebung dem Erleben einer realen Umgebung?
    überhaupt nicht ☐ ☐ ☐ ☐ ☐ ☐ ☐ vollständig

    (etwas)
13. Wie real erschien Ihnen die virtuelle Welt?
    wie eine vorgestellte Welt ☐ ☐ ☐ ☐ ☐ ☐ ☐ nicht zu unterscheiden von der realen Welt
14. Die virtuelle Welt erschien mir wirklicher als die reale Welt.
    trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

Trial 4 [Bedingung: _____]

A) Spezifische Einzelfragen: Ihr Erleben während des Ereignisses

Anleitung: Bitte kreisen Sie für jede der folgenden Fragen die Zahl ein, die Ihr Erleben während des soeben stattgefundenen Ereignisses am besten beschreibt.

Fragen:

1. Inwieweit haben Sie eine **Veränderung des Gewichts** der Hantel gespürt?

Keinerlei Veränderung ① ② ③ ④ ⑤ ⑥ ⑦ Eine sehr deutliche Veränderung

(Neutral)

2. Wie **realistisch** hat sich die Veränderung des Hantelgewichts angefühlt?

Überhaupt nicht realistisch ① ② ③ ④ ⑤ ⑥ ⑦ Vollkommen realistisch

(Neutral)

3. Bitte bewerten Sie das Ausmaß der **Diskrepanz** (des Auseinanderklaffens) zwischen dem, was Sie gesehen, und dem, was Sie gefühlt haben.

Keinerlei Diskrepanz ① ② ③ ④ ⑤ ⑥ ⑦ Eine sehr starke Diskrepanz

(Neutral)

4. Inwieweit hatten Sie das Gefühl, die virtuelle Hantel unter **Kontrolle** zu haben?

Überhaupt nicht unter Kontrolle ① ② ③ ④ ⑤ ⑥ ⑦ Vollkommen unter Kontrolle

(Neutral)

5. Das Objekt fühlte sich an, als ob es um ungefähr ___ **Kg** schwerer wurde (bitte eine Zahl eintragen)?

B) Igroup Presence Questionnaire (IPQ): Erleben in der virtuellen Umgebung

Anleitung: Bitte geben Sie für jede der folgenden Aussagen an, wie Sie die virtuelle Erfahrung empfunden haben. Kreuzen Sie für jede Zeile das Kästchen an, das Ihre Empfindung am besten beschreibt.

Fragen:

1. In der computererzeugten Welt hatte ich den Eindruck, dort gewesen zu sein.

überhaupt nicht ☐ ☐ ☐ ☐ ☐ ☐ ☐ sehr stark

2. Ich hatte das Gefühl, daß die virtuelle Umgebung hinter mir weitergeht.

trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

3. Ich hatte das Gefühl, nur Bilder zu sehen.

trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

4. Ich hatte nicht das Gefühl, in dem virtuellen Raum zu sein.

hatte nicht das Gefühl ☐ ☐ ☐ ☐ ☐ ☐ ☐ hatte das Gefühl

5. Ich hatte das Gefühl, in dem virtuellen Raum zu handeln statt etwas von außen zu bedienen.

trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

6. Ich fühlte mich im virtuellen Raum anwesend.

trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

7. Wie bewußt war Ihnen die reale Welt, während Sie sich durch die virtuelle Welt bewegten (z.B. Geräusche, Raumtemperatur, andere Personen etc.)?
   extrem bewußt ☐ ☐ ☐ ☐ ☐ ☐ ☐ unbewußt

   (mittelmäßig bewußt)

8. Meine reale Umgebung war mir nicht mehr bewußt.
   trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

9. Ich achtete noch auf die reale Umgebung.
   trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

10. Meine Aufmerksamkeit war von der virtuellen Welt völlig in Bann gezogen.
    trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

11. Wie real erschien Ihnen die virtuelle Umgebung?
    gar nicht real ☐ ☐ ☐ ☐ ☐ ☐ ☐ vollkommen real

    (weder noch)

12. Wie sehr glich Ihr Erleben der virtuellen Umgebung dem Erleben einer realen Umgebung?
    überhaupt nicht ☐ ☐ ☐ ☐ ☐ ☐ ☐ vollständig

    (etwas)

13. Wie real erschien Ihnen die virtuelle Welt?
    wie eine vorgestellte Welt ☐ ☐ ☐ ☐ ☐ ☐ ☐ nicht zu unterscheiden von der realen Welt

14. Die virtuelle Welt erschien mir wirklicher als die reale Welt.
    trifft gar nicht zu ☐ ☐ ☐ ☐ ☐ ☐ ☐ trifft völlig zu

Teilstrukturiertes Interview (Feedback)

F1: Wenn Sie an die verschiedenen Ereignisse zurückdenken, die Sie erlebt haben: Welches fühlte sich für Sie am **realistischsten oder überzeugendsten** an und was genau hat dieses Gefühl ausgelöst?

F2: Gab es umgekehrt auch ein Erlebnis, das sich besonders **unrealistisch, seltsam oder unnatürlich** angefühlt hat? Können Sie beschreiben, was daran „unstimmig" war?

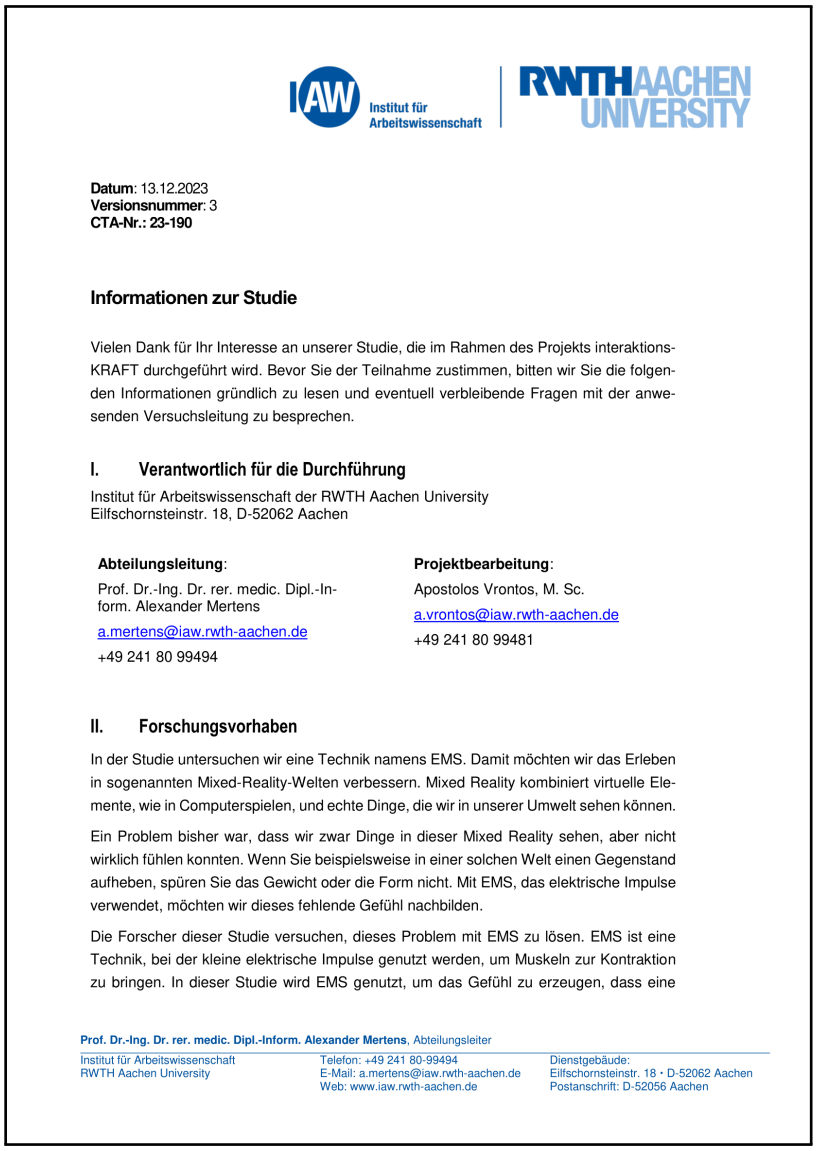
F3: Wenn Sie irgendeinen Aspekt des Systems oder der Empfindungen, die Sie gespürt haben, **ändern oder verbessern** könnten, was wäre das und warum?

F4: Gibt es abschließend noch etwas, das Sie über Ihre **Gesamterfahrung** mitteilen möchten, worüber wir noch nicht gesprochen haben?

ENDE.

10

E.1 Participant Information and Consent Form (Experiment 1)



Institut für Arbeitswissenschaft | RWTH AACHEN UNIVERSITY

Datum: 13.12.2023
Versionsnummer: 3
CTA-Nr.: 23-190

Informationen zur Studie

Vielen Dank für Ihr Interesse an unserer Studie, die im Rahmen des Projekts interaktionsKRAFT durchgeführt wird. Bevor Sie der Teilnahme zustimmen, bitten wir Sie die folgenden Informationen gründlich zu lesen und eventuell verbleibende Fragen mit der anwesenden Versuchsleitung zu besprechen.

I. Verantwortlich für die Durchführung

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Eilfschornsteinstr. 18, D-52062 Aachen

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II. Forschungsvorhaben

In der Studie untersuchen wir eine Technik namens EMS. Damit möchten wir das Erleben in sogenannten Mixed-Reality-Welten verbessern. Mixed Reality kombiniert virtuelle Elemente, wie in Computerspielen, und echte Dinge, die wir in unserer Umwelt sehen können.

Ein Problem bisher war, dass wir zwar Dinge in dieser Mixed Reality sehen, aber nicht wirklich fühlen konnten. Wenn Sie beispielsweise in einer solchen Welt einen Gegenstand aufheben, spüren Sie das Gewicht oder die Form nicht. Mit EMS, das elektrische Impulse verwendet, möchten wir dieses fehlende Gefühl nachbilden.

Die Forscher dieser Studie versuchen, dieses Problem mit EMS zu lösen. EMS ist eine Technik, bei der kleine elektrische Impulse genutzt werden, um Muskeln zur Kontraktion zu bringen. In dieser Studie wird EMS genutzt, um das Gefühl zu erzeugen, dass eine

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externe Kraft auf den Arm wirkt. Dies könnte beispielsweise das Gefühl simulieren, ein virtuelles Objekt zu heben.

Die Studie wird in mehreren Schritten durchgeführt, bei denen die Versuchsperson verschiedene Stufen von EMS-Stimulationen durchlaufen und dabei ihre Empfindungen dokumentieren. Ziel ist es, zu verstehen, wie verschiedene Stufen der EMS-Stimulation die Wahrnehmung von Kraft und Gewicht beeinflussen, und diese Erkenntnisse dann zu nutzen, um die haptische Feedbacktechnologie in Mixed-Reality-Umgebungen zu verbessern.

Im Wesentlichen geht es in dieser Studie darum, eine bessere, realistischere und immersivere Benutzererfahrung in Mixed-Reality-Umgebungen zu ermöglichen. Dies könnte eine Vielzahl von Anwendungen verbessern, von Videospielen und interaktiven Medien bis hin zu Trainings- und Rehabilitationsprogrammen.

III. Versuchsaufbau

Die Versuchsanordnung setzt sich aus verschiedenen Geräten zusammen. Als Hauptinstrument dient das Stimulationssystem P24 Science (CE-zertifiziert) von Hasomed. Mit diesem Gerät werden wir Ihre Muskeln elektrisch stimulieren, um eine künstliche Aktivierung hervorzurufen. Zusätzlich wird ein Kraftmessgerät (CE-zertifiziert) von Norakon verwendet, um die durch die Muskelaktivierung erzeugte Kraft in einem Teil der Studie zu messen.

Ein Laptop (CE-zertifiziert) kommt ebenfalls zum Einsatz. Mit diesem steuern wir die Intensität der elektrischen Stimulation, die vom Stimulationssystem ausgeht. Des Weiteren verwenden wir eine Waage von Beurer (CE-zertifiziert), um Körperparameter wie Ihren Körperfettanteil, die Knochenmasse und den Flüssigkeitsanteil zu bestimmen. Zum Versuchsaufbau gehören auch zwei Gewichtsplatten, die 2 Kg und 3 Kg wiegen.

Für die Erfassung Ihrer körperlichen Eigenschaften zu Beginn der Studie setzen wir außerdem eine Körpergröße-Messskala, ein Umfangmessgerät und ein Lineal ein. Die genauen Details dazu finden Sie im Abschnitt "Ablauf der Studie".

IV. Ablauf der Studie

Die Studie wird gemäß der nachfolgend beschriebenen Schritte ablaufen:

1) Persönliches Aufklärungsgespräch: Hier haben Sie die Möglichkeit, umfassende Rückfragen zu dieser Studie zu stellen und weitere Informationen zu erhalten, um Ihre Teilnahme zu verstehen.

2) Bedenkzeit und Entscheidung: Nach dem Gespräch erhalten Sie ausreichend Zeit, um über Ihre Teilnahme an der Studie nachzudenken und eine informierte Entscheidung zu treffen.
3) Einverständniserklärung: Bevor die Studie beginnt, werden Sie gebeten, ein Dokument zu unterschreiben, das bestätigt, dass Sie alles verstanden haben und freiwillig teilnehmen möchten.
4) Versuchsdurchführung:
   a) Ausfüllen eines Fragebogens zu körperlichen Eigenschaften und demographischen Daten: Hier werden wir Sie bitten, einen Fragebogen zu vervollständigen, der sich auf Aspekte Ihrer körperlichen Charakteristiken (Gewicht, Körperfettanteil, Knochenmasse, Körperflüssigketisanteil, Massenanteil, Körpergröße, maximal generierte Kraft durch willkürliche Aktivierung des Bizeps- und Trizeps-Muskels, Länge des Trizeps-Muskels, Länge des Oberarms, Länge des Unterarms, Umfang des Oberarms) und Ihrer demographischen Daten (Alter, Geschlecht) konzentriert. Genauere Details zum Datenschutz und wie wir mit diesen Informationen umgehen, finden Sie im Abschnitt "Informationen zum Datenschutz".
   b) Individuelle Kalibrierung der Stimulationsintensität: Die Stärke des elektrischen Stroms, der nötig ist, um einen Muskel zu aktivieren, ist bei jedem Menschen unterschiedlich. Daher beginnen wir in diesem Studienteil mit einem schwachen Strom, der schrittweise erhöht wird. Dies geschieht vor allem an zwei Muskeln: Ihrem Trizeps (auf der Rückseite Ihres Oberarms) und dem Extensor carpi ulnaris (auf der Oberseite Ihres Unterarms). Wir suchen dabei nach einem optimalen Bereich, der zwischen zwei Punkten liegt: dem Punkt, an dem Ihr Muskel beginnt, sich zu straffen und dem Punkt, an dem eine weitere Steigerung des Stroms für Sie unangenehm wäre. Sie bestimmen diesen zweiten Punkt selbst, indem Sie uns einfach "Stop" sagen, bevor das Gefühl für Sie unangenehm wird. Die so ermittelten Werte werden in den folgenden Teilen der Studie genutzt, um die Grenzen der Stimulation individuell auf Sie anzupassen.
   c) Nun beginnt der Kern der Studie, der aus vier Abschnitten besteht.
      i) Im ersten Abschnitt halten Sie mit Ihrer dominanten Hand eine Gewichtsplatte, während der gleiche Arm stimuliert wird. Im Anschluss stellen wir Ihnen einige spezifische Fragen. Dabei möchten wir herausfinden, wie die elektrische Stimulation Ihre Wahrnehmung des Gewichts der Platte beeinflusst.
      ii) Im zweiten Abschnitt halten Sie mit Ihrer dominanten Hand eine leichte Gewichtsplatte und mit Ihrer nicht-dominanten Hand eine schwerere Gewichtsplatte. Unser Ziel hierbei ist es zu ermitteln, welche Stimulation auf der dominanten Seite dazu führt, dass sich das leichtere Objekt genauso schwer anfühlt wie das schwerere Objekt.
      iii) Der dritte Abschnitt ist ähnlich wie der zweite: Sie halten erneut eine leichte Gewichtsplatte mit Ihrer dominanten Hand und eine schwerere Gewichtsplatte mit Ihrer nicht-dominanten Hand. Diesmal senden wir jedoch zufällige Stromstärken (mal niedriger, mal höher, aber immer innerhalb Ihres individuellen Bereichs) an Ihre Muskulatur. Sie werden gebeten anzugeben, ob und wann sich das leichtere Objekt schwerer anfühlte als das schwerere.
      iv) Im vierten Abschnitt wird Ihr Trizepsmuskel stimuliert und wir messen gleichzeitig, wie viel Kraft durch diese künstliche Aktivierung erzeugt wird. Dazu verwenden wir ein Kraftmessgerät, das mit einem Seil verbunden ist, welches Sie mit der Hand

der stimulierten Seite greifen. Durch die elektrische Stimulation Ihres Trizeps wird Ihr Unterarm nach unten gezogen, wie in der unteren Abbildung dargestellt. Diese Kraft, die Ihren Arm nach unten zieht, wird mit dem Kraftmessgerät erfasst.

Die Reihenfolge der vier Abschnitte wird zufällig bestimmt. Auf diese Weise können wir sicherstellen, dass die Ergebnisse eines Abschnitts keinen systematischen Einfluss auf die Ergebnisse der anderen haben.

V. Risiken

Die Teilnahme an dieser Studie ist mit gewissen Risiken verbunden, die im Zusammenhang mit der Anwendung von Elektromuskelstimulation (EMS) stehen oder mit dem Versuchsaufbau verknüpft sind. Dennoch sind die Risiken der EMS sehr gering und treten nur bei äußerst hoher Intensität und langer Dauer der Stimulation auf:

• Hautirritationen: Sehr selten kann es zu Hautirritationen kommen, vor allem wenn eine äußerst hohe Intensität und lange Dauer der EMS-Stimulation eingesetzt wird.

• Hautrötungen: Ebenso selten können Hautrötungen auftreten, vor allem bei Verwendung von sehr hohen Stimulationsintensitäten über eine längere Zeit.

• Muskelkater: Wie nach intensiver körperlicher Aktivität kann es durch die Stimulation der Muskulatur zu Muskelkater kommen. Dies ist eine normale Reaktion des Körpers auf ungewohnte oder intensive Belastung.

Bitte beachten Sie, dass diese Nebenwirkungen in der Regel nur vorübergehend sind und nach Beendigung der Stimulation abklingen.

Um das Risiko des Herabfallens der Gewichte zu eliminieren und die Sicherheit während der Durchführung zu gewährleisten, werden die Gewichtsplatten mittels eines robusten Seils gesichert. Dieses Seil begrenzt den potenziellen Fall der Platten auf eine maximale Höhe von etwa 30 Zentimetern über dem Bodenniveau. Zusätzlich ist die Arbeitsfläche mit einem speziellen Gummimaterial ausgelegt, das ein mögliches Weiterrollen der Platten effektiv verhindert, falls diese auf die Tischoberfläche gelangen sollten.

Für die weiteren in der Studie verwendeten Geräte, wie im Abschnitt "Versuchsaufbau" beschrieben, sind keine spezifischen Risiken bekannt.

Es besteht kein COVID-19-Infektionsrisiko, was über ein im Alltag zu erwartendes Maß hinausgeht.

VI. Versuchspersonen

Wir planen, 70 Versuchspersonen im Alter zwischen 18 und 64 Jahren für die Teilnahme an der Studie zu gewinnen. Die Anzahl der Versuchspersonen ergibt sich aus der statistischen Stichprobengrößenplanung. Für Ihre Teilnahme an der Studie, die voraussichtlich etwa 2 Stunden in Anspruch nehmen wird, erhalten Sie eine Aufwandsentschädigung von 30€ (in bar). Die Vergütung efolgt am Ende der Studie. Die Finanzierung der Studie erfolgt durch das Bundesministerium für Bildung und Forschung (BMBF). Bei weiteren Fragen zur Förderung können Sie sich hier wenden: vdi@vdi.de / Förderkennzeichen: 16SV8727.

Die Rekrutierung der Versuchspersonen für diese Studie erfolgt hauptsächlich durch das Anbringen von Informationszetteln in unserem Institut sowie an geeigneten Orten innerhalb der Universität.

1. Einschlusskriterien

Versuchspersonen können an dieser Studie teilnehmen, sofern sie die folgenden Kriterien erfüllen:

- Sie sind mindestens 18 Jahre und maximal 64 Jahre alt.
- Sie sprechen Deutsch auf einem kommunikationsfähigen Niveau (mindestens B2).

2. Ausschlußkriterien

Die Teilnahme an der Studie setzt voraus, dass **keine** der folgenden Bedingungen vorliegt:

- Schwangerschaft
- Vorhandensein von Herz- oder anderen Schrittmachergeräten
- Verdachtsfälle oder diagnostizierte Herzprobleme
- Frische Naben, Wunden, Inflammation, Hauterkrankung, Krebsläsionen an der Stelle der Stimulation
- Epileptische Anfälle

3. Risiko-/Nutzenbewertung

Die Entscheidung zur Teilnahme an dieser Studie sollte auf einer sorgfältigen Abwägung der potenziellen Risiken und Vorteile basieren. Wie bei jeder Studie, birgt auch diese bestimmte Risiken, die bereits dargelegt wurden. Dazu gehören Hautirritationen und Hautrötungen, die sehr selten auftreten und nur bei äußerst hoher Intensität und Dauer der Elektromuskelstimulation (EMS) beobachtet werden können.

Die potenziellen Vorteile der Teilnahme an dieser Studie hängen stark von den individuellen Umständen ab. Für viele Teilnehmer kann die Teilnahme an dieser Studie eine Möglichkeit bieten, einen Beitrag zur Forschung und zur Verbesserung des Verständnisses der Auswirkungen von EMS auf die Wahrnehmung von Gewicht und Kraft zu leisten. Darüber hinaus können Teilnehmer durch ihre Beteiligung ein besseres Verständnis für ihre körperliche Leistungsfähigkeit und ihre Reaktion auf EMS erlangen.

Es ist wichtig zu betonen, dass diese Studie in erster Linie wissenschaftlichen Zwecken dient und somit den Probanden nur geringe direkte Vorteile bietet, die Ergebnisse jedoch einen hohen gesamtgesellschaftlichen Mehrwert darstellen und in Zukunft einen wichtigen Beitrag zur Behandlung von Krankheiten oder zur Verbesserung der körperlichen Leistungsfähigkeit liefern.

VII. Versicherung

Die Studienverantwortlichen sind haftpflichtversichert für den Fall, dass Sie durch deren Verschulden einen Schaden erleiden. Unverschuldete Gesundheitsschäden, die während oder im Zusammenhang mit der Studie entstehen, sind über diese Betriebshaftpflichtversicherung nicht versichert.

Ein Versicherungsschutz in Form von Probandenversicherung oder Wege-Unfall-Versicherung besteht nicht. Sie sind während der Studie also nicht über das Institut für Arbeitswissenschaft durch gegen Sie verursachte Schäden versichert.

VIII. Freiwilligkeit der Teilnahme

Ihre Teilnahme an dieser Studie ist freiwillig. Sie können jederzeit ohne Angabe von Gründen die Teilnahme beenden. Dadurch entstehen Ihnen keine Nachteile.

IX. Informationen zum Datenschutz

Ihre personenbezogenen Daten werden ausschließlich von den an der Studie beteiligten Mitarbeitern des Studienzentrums verarbeitet. Diese sind zur Wahrung der Vertraulichkeit verpflichtet.

Im Rahmen der Studie werden Ihre Daten einschließlich der Daten über Alter, Geschlecht, Gewicht, Körperfettanteil, Knochenmasse, Körperflüssigkeitsanteil, Körpergröße, maximal generierte Kraft durch willkürliche Aktivierung des Bizeps- und Trizeps-Muskels, Länge des Trizeps-Muskels, Länge des Oberarms, Länge des Unterarms und Umfang des Oberarms anonymisiert aufgezeichnet. Dies bewirkt, dass diejenigen, die (im Forschungszusammenhang) Daten verarbeiten oder einsehen, diese nicht Ihnen als Person zuordnen können. Damit ist es unmöglich die Studiendaten weiterhin individuell zuzuordnen.

Die im Rahmen der Studie erhobenen Daten werden von einem elektronischen Datensystem erfasst und statistisch ausgewertet. Nach Beendigung der Studie werden alle Daten nach den derzeit gültigen Richtlinien entsprechend gespeichert und archiviert. Die Verantwortung für die Einhaltung des Datenschutzes im Rahmen des elektronischen Datensystems liegt bei dem Institut und Lehrstuhl für Arbeitswissenschaft der RWTH Aachen, Eilfschornsteinstraße 18, 52062 Aachen.

Die Bearbeitung der erhobenen Daten erfolgt in Verantwortung von Prof. Dr.-Ing. Dr. rer. medic. Dipl.-Inform. Alexander Mertens, Abteilungsleitung, Institut und Lehrstuhl für Arbeitswissenschaft, Eilfschornsteinstraße 18, 52062 Aachen. Sie haben das Recht, Einsicht in Ihre Daten zu nehmen, die während der Studie erhoben werden.

Sollten Sie dabei Fehler in Ihren Daten feststellen, so haben Sie das Recht, diese korrigieren zu lassen. Weiterhin haben Sie das Recht auf Auskunft und Überlassung einer Kopie Ihrer Daten. Sie haben darüber hinaus das Recht sich bei einer Aufsichtsbehörde (siehe unten Punkt „Datenschutzaufsichtsbehörde“) über den Umgang mit Ihren Daten zu beschweren.

Die anonymisierten Daten werden dem Auftraggeber der Studie oder einer von diesem beauftragten Stelle zu wissenschaftlichen Zwecken zur Verfügung gestellt. Die Weitergabe der anonymisierten Daten erfolgt im Falle eines Antrags auf Zulassung weiterhin auch an den Antragsteller. Auch bei der Übergabe von anonymisierten Daten an einen Nicht-EU-Mitgliedstaat, z.B. für die internationale Vorlage bei den entsprechenden Behörden, werden Ihre personenbezogenen Daten vertraulich behandelt.

Adressen und Kontakte

Abteilungsleitung:

Prof. Dr.-Ing. Dr. rer. medic. Dipl.-Inform. Alexander Mertens
Institut und Lehrstuhl für Arbeitswissenschaft RWTH Aachen
Eilfschornsteinstraße 18
52062 Aachen
Tel: 0241 80 99494
Fax: 0241 80 92131

Datenschutzbeauftragter der Studienleitung:

Datenschutzbeauftragter der RWTH Aachen
E-Mail: dsb@rwth-aachen.de
Telefon: +49 241 80 93665

Datenschutzbeauftragter des Prüfzentrums:

Datenschutzbeauftragter der RWTH Aachen
E-Mail: dsb@rwth-aachen.de
Telefon: +49 241 80 93665

Datenschutzaufsichtsbehörde (Studienleitung):

Landesbeauftragten für Datenschutz und Informationsfreiheit Nordrhein-Westfalen
E-Mail: poststelle@ldi.nrw.de

Verantwortlicher für die Verarbeitung Ihrer Daten:
Prof. Dr.-Ing. Dr. rer. medic. Dipl.-Inform. Alexander Mertens
Institut und Lehrstuhl für Arbeitswissenschaft RWTH Aachen
Eilfschornsteinstraße 18
52062 Aachen
Tel: 0241 80 99494
Fax: 0241 80 92131

X. Einwilligungserklärung

Titel der Studie: Objektive und subjektive Messung der mittels Elektromyostimulation erzeugten Kraftwahrnehmung am Bizeps Muskel

Name der Versuchsperson in Druckbuchstaben:……...

- Ich bin von Herrn / Frau _____ über Wesen, Bedeutung und Tragweite der Studie sowie die sich für mich daraus ergebenden Anforderungen aufgeklärt worden. Ich habe darüber hinaus den Text der Probandeninformation und dieser Einwilligungserklärung gelesen.
- Ich hatte ausreichend Zeit, Fragen zu stellen und mich zu entscheiden. Aufgetretene Fragen wurden mir vom Studienleiter beantwortet.
- Ich weiß, dass ich meine freiwillige Mitwirkung jederzeit beenden kann, ohne dass mir daraus Nachteile entstehen.
- Keine der Ausschlusskriterien liegt bei mir vor!

Ich erkläre mich bereit, an der Studie teilzunehmen.

Datenschutzerklärung

1. Ich willige ein, dass personenbezogene Daten über mich, insbesondere diese in Kapitel „Informationen zum Datenschutz“, wie in der Informationsschrift beschrieben erhoben und in Papierform sowie auf elektronischen Datenträgern beim Institut für die Arbeitswissenschaft aufgezeichnet werden.

Soweit erforderlich, dürfen die erhobenen Daten anonymisiert weitergegeben werden:

a) an M.Sc. Apostolos Vrontos oder von diesem beauftragte Stellen zum Zweck der wissenschaftlichen Auswertung,
b) im Falle unerwünschter Ereignisse: an das Bundesministerium für Bildung und Forschung, an die jeweils zuständige Ethikkommission und zuständige Behörden sowie von dieser an die Europäische Datenbank.

2. Ich bin darüber aufgeklärt worden, dass ich meine Einwilligung jederzeit widerrufen kann. Im Falle des Widerrufs werden keine weiteren Daten mehr erhoben. Ich kann in diesem Fall die Löschung der Daten verlangen.

3. Ich willige ein, dass die Daten nach Beendigung oder Abbruch der Studie mindestens 3 Jahre aufbewahrt werden.

Ich willige in die Verarbeitung der genannten Daten ein.

Ein Exemplar der Probandeninformation und der Einwilligungserklärung habe ich erhalten. Ein Exemplar verbleibt im Prüfzentrum.

Unterschrift der Versuchsperson

_____

(Name und Vorname in Druckschrift)

_____ _____

(Datum) (Prüfer Unterschrift)

E.2 Participant Information and Consent Form (Experiment 2)

Institut für Arbeitswissenschaft | RWTH AACHEN UNIVERSITY

Datum: 31.03.2025
Versionsnummer: 1

Informationen zur Studie

Vielen Dank für Ihr Interesse an unserer Studie, die im Rahmen des Projekts interaktionsKRAFT durchgeführt wird. Bevor Sie der Teilnahme zustimmen, bitten wir Sie die folgenden Informationen gründlich zu lesen und eventuell verbleibende Fragen mit der anwesenden Versuchsleitung zu besprechen.

I. Verantwortlich für die Durchführung

Institut für Arbeitswissenschaft der RWTH Aachen University
Eilfschornsteinstr. 18, D-52062 Aachen

Abteilungsleitung:
Prof. Dr.-Ing. Dr. rer. medic. Dipl.-Inform. Alexander Mertens
a.mertens@iaw.rwth-aachen.de
+49 241 80 99494

Projektbearbeitung:
Apostolos Vrontos, M. Sc.
a.vrontos@iaw.rwth-aachen.de
+49 241 80 99481

II. Forschungsvorhaben

In der Studie untersuchen wir eine Technik namens EMS. Damit möchten wir das Erleben in sogenannten Mixed-Reality-Welten verbessern. Mixed Reality kombiniert virtuelle Elemente, wie in Computerspielen, und echte Dinge, die wir in unserer Umwelt sehen können.

Ein Problem bisher war, dass wir zwar Dinge in dieser Mixed Reality sehen, aber nicht wirklich fühlen konnten. Wenn Sie beispielsweise in einer solchen Welt einen Gegenstand aufheben, spüren Sie das Gewicht oder die Form nicht. Mit EMS, das elektrische Impulse verwendet, möchten wir dieses fehlende Gefühl nachbilden.

Die Forscher dieser Studie versuchen, dieses Problem mit EMS zu lösen. EMS ist eine Technik, bei der kleine elektrische Impulse genutzt werden, um Muskeln zur Kontraktion zu bringen. In dieser Studie wird EMS genutzt, um das Gefühl zu erzeugen, dass eine externe Kraft auf den Arm wirkt. Dies könnte beispielsweise das Gefühl simulieren, ein virtuelles Objekt zu heben.

Prof. Dr.-Ing. Dr. rer. medic. Dipl.-Inform. Alexander Mertens, Abteilungsleiter

Institut für Arbeitswissenschaft
RWTH Aachen University

Telefon: +49 241 80-99494
E-Mail: a.mertens@iaw.rwth-aachen.de
Web: www.iaw.rwth-aachen.de

Dienstgebäude:
Eilfschornsteinstr. 18 • D-52062 Aachen
Postanschrift: D-52056 Aachen

Die Studie wird in mehreren Schritten durchgeführt, bei denen die Versuchsperson verschiedene Stufen von EMS-Stimulationen durchlaufen und dabei ihre Empfindungen dokumentieren. Ziel ist es, zu verstehen, wie verschiedene Stufen der EMS-Stimulation die Wahrnehmung von Kraft und Gewicht beeinflussen, und diese Erkenntnisse dann zu nutzen, um die haptische Feedbacktechnologie in Mixed-Reality-Umgebungen zu verbessern.

Im Wesentlichen geht es in dieser Studie darum, eine bessere, realistischere und immersivere Benutzererfahrung in Mixed-Reality-Umgebungen zu ermöglichen. Dies könnte eine Vielzahl von Anwendungen verbessern, von Videospielen und interaktiven Medien bis hin zu Trainings- und Rehabilitationsprogrammen.

III. Versuchsaufbau

Die Versuchsanordnung setzt sich aus verschiedenen Geräten zusammen. Als Hauptinstrument dient das Stimulationssystem P24 Science (CE-zertifiziert) von Hasomed. Mit diesem Gerät werden wir Ihre Muskeln elektrisch stimulieren, um eine künstliche Aktivierung hervorzurufen.

Ein Laptop (CE-zertifiziert) kommt ebenfalls zum Einsatz. Mit diesem steuern wir die Intensität der elektrischen Stimulation, die vom Stimulationssystem ausgeht. Des Weiteren verwenden wir eine Waage von Beurer (CE-zertifiziert), um Körpergewicht und eine Körpergröße-Messskala um Körpergröße zu messen. Darüber hinaus gehören zum Versuchsaufbau drei Kurzhanteln mit einem Gewicht von 1 kg, 3 kg und 5 kg sowie ein Umfangmessgerät und ein Messband, mit denen wir die Armdimensionen erfassen. Ergänzend setzen wir einen Handgripper ein, um die Greifkraft zu bestimmen.

IV. Ablauf der Studie

Die Studie wird gemäß der nachfolgend beschriebenen Schritte ablaufen:

1) Persönliches Aufklärungsgespräch: Hier haben Sie die Möglichkeit, umfassende Rückfragen zu dieser Studie zu stellen und weitere Informationen zu erhalten, um Ihre Teilnahme zu verstehen.
2) Bedenkzeit und Entscheidung: Nach dem Gespräch erhalten Sie ausreichend Zeit, um über Ihre Teilnahme an der Studie nachzudenken und eine informierte Entscheidung zu treffen.
3) Einverständniserklärung: Bevor die Studie beginnt, werden Sie gebeten, ein Dokument zu unterschreiben, das bestätigt, dass Sie alles verstanden haben und freiwillig teilnehmen möchten.
4) Versuchsdurchführung:

a) Ausfüllen eines Fragebogens zu körperlichen Eigenschaften und demographischen Daten: Hier werden wir Sie bitten, einen Fragebogen zu vervollständigen, der sich auf Aspekte Ihrer körperlichen Charakteristiken (dominante Seite, Gewicht, Körpergröße, Länge des Oberarms, Länge des Unterarms, Umfang des Oberarms, maximale Greifkraft) und Ihrer demographischen Daten (Alter, Geschlecht) konzentriert. Genauere Details zum Datenschutz und wie wir mit diesen Informationen umgehen, finden Sie im Abschnitt "Informationen zum Datenschutz".

b) Individuelle Kalibrierung der Stimulationsintensität: Die Stärke des elektrischen Stroms, der nötig ist, um einen Muskel zu aktivieren, ist bei jedem Menschen unterschiedlich. Daher beginnen wir in diesem Studienteil mit einem schwachen Strom, der schrittweise erhöht wird. Dies geschieht vor allem an zwei Muskeln: Ihrem Trizeps (auf der Rückseite Ihres Oberarms) und dem Extensor carpi ulnaris (auf der Oberseite Ihres Unterarms). Wir suchen dabei nach einem optimalen Bereich, der zwischen zwei Punkten liegt: dem Punkt, an dem Ihr Muskel beginnt, sich zu straffen und dem Punkt, an dem eine weitere Steigerung des Stroms für Sie unangenehm wäre. Sie bestimmen diesen zweiten Punkt selbst, indem Sie uns einfach "Stop" sagen, bevor das Gefühl für Sie unangenehm wird. Die so ermittelten Werte werden in den folgenden Teilen der Studie genutzt, um die Grenzen der Stimulation individuell auf Sie anzupassen.

c) Im Hauptteil der Untersuchung vergleichen Sie Gewichte in Form von Kurzhanteln unter verschiedenen Bedingungen. Zu Beginn wird eine Seite leichter sein. Durch Elektromyostimulation wird die wahrgenommene Belastung auf dieser Seite schrittweise erhöht, indem die Stimulationsintensität gesteigert wird, bis beide Gewichte für Sie gleich schwer erscheinen. Dieser Vorgang wird mit unterschiedlichen Gewichten und Armhaltungen wiederholt, beispielsweise mit einem Ellenbogenwinkel von 90 Grad oder 45 Grad. Ziel ist es, einen quantitativen Zusammenhang zwischen der Stimulationsintensität, der Armhaltung und Ihrer Kraftempfindung herzustellen.

   Die Reihenfolge der Bedingungen wird zufällig festgelegt. Dadurch stellen wir sicher, dass die Ergebnisse eines Abschnitts keinen systematischen Einfluss auf die nachfolgenden Abschnitte ausüben und die Daten unabhängig voneinander bleiben.

V. Risiken

Die Teilnahme an dieser Studie ist mit gewissen Risiken verbunden, die im Zusammenhang mit der Anwendung von Elektromuskelstimulation (EMS) stehen oder mit dem Versuchsaufbau verknüpft sind. Dennoch sind die Risiken der EMS sehr gering und treten nur bei äußerst hoher Intensität und langer Dauer der Stimulation auf:

Sehr selten kann es zu Hautirritationen kommen, vor allem wenn eine äußerst hohe Intensität und lange Dauer der EMS-Stimulation eingesetzt wird.

Ebenso selten können Hautrötungen auftreten, vor allem bei Verwendung von sehr hohen Stimulationsintensitäten über eine längere Zeit.

Wie nach intensiver körperlicher Aktivität kann es durch die Stimulation der Muskulatur zu Muskelkater kommen. Dies ist eine normale Reaktion des Körpers auf ungewohnte oder intensive Belastung.

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1. Einschlusskriterien

Versuchspersonen können an dieser Studie teilnehmen, sofern sie die folgenden Kriterien erfüllen:

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- Sie sprechen Deutsch auf einem kommunikationsfähigen Niveau (mindestens B2).

2. Ausschlußkriterien

Die Teilnahme an der Studie setzt voraus, dass **keine** der folgenden Bedingungen vorliegt:

- Schwangerschaft
- Vorhandensein von Herz- oder anderen Schrittmachergeräten
- Verdachtsfälle oder diagnostizierte Herzprobleme
- Frische Naben, Wunden, Inflammation, Hauterkrankung, Krebsläsionen an der Stelle der Stimulation
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Die Entscheidung zur Teilnahme an dieser Studie sollte auf einer sorgfältigen Abwägung der potenziellen Risiken und Vorteile basieren. Wie bei jeder Studie, birgt auch diese bestimmte Risiken, die bereits dargelegt wurden. Dazu gehören Hautirritationen und Hautrötungen, die sehr selten auftreten und nur bei äußerst hoher Intensität und Dauer der Elektromuskelstimulation (EMS) beobachtet werden können.

Die potenziellen Vorteile der Teilnahme an dieser Studie hängen stark von den individuellen Umständen ab. Für viele Teilnehmer kann die Teilnahme an dieser Studie eine Möglichkeit bieten, einen Beitrag zur Forschung und zur Verbesserung des Verständnisses der Auswirkungen von EMS auf die Wahrnehmung von Gewicht und Kraft zu leisten. Darüber

hinaus können Teilnehmer durch ihre Beteiligung ein besseres Verständnis für ihre körperliche Leistungsfähigkeit und ihre Reaktion auf EMS erlangen.

Es ist wichtig zu betonen, dass diese Studie in erster Linie wissenschaftlichen Zwecken dient und somit den Probanden nur geringe direkte Vorteile bietet, die Ergebnisse jedoch einen hohen gesamtgesellschaftlichen Mehrwert darstellen und in Zukunft einen wichtigen Beitrag zur Behandlung von Krankheiten oder zur Verbesserung der körperlichen Leistungsfähigkeit liefern.

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VIII. Freiwilligkeit der Teilnahme

Ihre Teilnahme an dieser Studie ist freiwillig. Sie können jederzeit ohne Angabe von Gründen die Teilnahme beenden. Dadurch entstehen Ihnen keine Nachteile.

IX. Informationen zum Datenschutz

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Im Rahmen der Studie werden Ihre Daten (siehe Abschnitt IV.) anonymisiert aufgezeichnet. Dies bewirkt, dass diejenigen, die (im Forschungszusammenhang) Daten verarbeiten oder einsehen, diese nicht Ihnen als Person zuordnen können. Damit ist es unmöglich die Studiendaten weiterhin individuell zuzuordnen.

Die im Rahmen der Studie erhobenen Daten werden von einem elektronischen Datensystem erfasst und statistisch ausgewertet. Nach Beendigung der Studie werden alle Daten nach den derzeit gültigen Richtlinien entsprechend gespeichert und archiviert. Die Verant-

wortung für die Einhaltung des Datenschutzes im Rahmen des elektronischen Datensystems liegt bei dem Institut und Lehrstuhl für Arbeitswissenschaft der RWTH Aachen, Eilfschornsteinstraße 18, 52062 Aachen.

Die Bearbeitung der erhobenen Daten erfolgt in Verantwortung von Prof. Dr.-Ing. Dr. rer. medic. Dipl.-Inform. Alexander Mertens, Abteilungsleitung, Institut und Lehrstuhl für Arbeitswissenschaft, Eilfschornsteinstraße 18, 52062 Aachen. Sie haben das Recht, Einsicht in Ihre Daten zu nehmen, die während der Studie erhoben werden.

Sollten Sie dabei Fehler in Ihren Daten feststellen, so haben Sie das Recht, diese korrigieren zu lassen. Weiterhin haben Sie das Recht auf Auskunft und Überlassung einer Kopie Ihrer Daten. Sie haben darüber hinaus das Recht sich bei einer Aufsichtsbehörde (siehe unten Punkt „Datenschutzaufsichtsbehörde“) über den Umgang mit Ihren Daten zu beschweren.

Die anonymisierten Daten werden dem Auftraggeber der Studie oder einer von diesem beauftragten Stelle zu wissenschaftlichen Zwecken zur Verfügung gestellt. Die Weitergabe der anonymisierten Daten erfolgt im Falle eines Antrags auf Zulassung weiterhin auch an den Antragsteller. Auch bei der Übergabe von anonymisierten Daten an einen Nicht-EU-Mitgliedstaat, z.B. für die internationale Vorlage bei den entsprechenden Behörden, werden Ihre personenbezogenen Daten vertraulich behandelt.

Adressen und Kontakte

Abteilungsleitung:

Prof. Dr.-Ing. Dr. rer. medic. Dipl.-Inform. Alexander Mertens
Institut und Lehrstuhl für Arbeitswissenschaft RWTH Aachen
Eilfschornsteinstraße 18
52062 Aachen
Tel: 0241 80 99494
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Datenschutzbeauftragter der Studienleitung:

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Datenschutzaufsichtsbehörde (Studienleitung):
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E-Mail: poststelle@ldi.nrw.de

Verantwortlicher für die Verarbeitung Ihrer Daten:
Prof. Dr.-Ing. Dr. rer. medic. Dipl.-Inform. Alexander Mertens
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X. Einwilligungserklärung

Titel der Studie: Quantitative Messung der mittels Elektromyostimulation erzeugten Kraftwahrnehmung am Arm

Name der Versuchsperson in Druckbuchstaben:……...

- Ich bin von Herrn / Frau _____ über Wesen, Bedeutung und Tragweite der Studie sowie die sich für mich daraus ergebenden Anforderungen aufgeklärt worden. Ich habe darüber hinaus den Text der Probandeninformation und dieser Einwilligungserklärung gelesen.
- Ich hatte ausreichend Zeit, Fragen zu stellen und mich zu entscheiden. Aufgetretene Fragen wurden mir vom Studienleiter beantwortet.
- Ich weiß, dass ich meine freiwillige Mitwirkung jederzeit beenden kann, ohne dass mir daraus Nachteile entstehen.
- Keine der Ausschlusskriterien liegt bei mir vor!

Ich erkläre mich bereit, an der Studie teilzunehmen.

Datenschutzerklärung

1. Ich willige ein, dass personenbezogene Daten über mich, insbesondere diese in Kapitel „Informationen zum Datenschutz“, wie in der Informationsschrift beschrieben erhoben und in Papierform sowie auf elektronischen Datenträgern beim Institut für die Arbeitswissenschaft aufgezeichnet werden.

Soweit erforderlich, dürfen die erhobenen Daten anonymisiert weitergegeben werden:

a) an M.Sc. Apostolos Vrontos oder von diesem beauftragte Stellen zum Zweck der wissenschaftlichen Auswertung,
b) im Falle unerwünschter Ereignisse: an das Bundesministerium für Bildung und Forschung, an die jeweils zuständige Ethikkommission und zuständige Behörden sowie von dieser an die Europäische Datenbank.

2. Ich bin darüber aufgeklärt worden, dass ich meine Einwilligung jederzeit widerrufen kann. Im Falle des Widerrufs werden keine weiteren Daten mehr erhoben. Ich kann in diesem Fall die Löschung der Daten verlangen.

3. Ich willige ein, dass die Daten nach Beendigung oder Abbruch der Studie mindestens 3 Jahre aufbewahrt werden.

Ich willige in die Verarbeitung der genannten Daten ein.

Ein Exemplar der Probandeninformation und der Einwilligungserklärung habe ich erhalten. Ein Exemplar verbleibt im Prüfzentrum.

_____

(Name der Versuchsperson in Druckschrift)

_____ _____

(Datum & Unterschrift der Versuchsperson) (Prüfer Unterschrift)

E.3 Participant Information and Consent Form (Experiment 3)

Datum: 04.08.2025
Versionsnummer: 1

Informationen zur Studie

Vielen Dank für Ihr Interesse an unserer Studie. Bevor Sie der Teilnahme zustimmen, bitten wir Sie, die folgenden Informationen gründlich zu lesen und eventuell verbleibende Fragen mit der anwesenden Versuchsleitung zu besprechen.

I. Verantwortlich für die Durchführung

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II. Forschungsvorhaben

In dieser Studie untersuchen wir, wie wir das Erleben in der Virtuellen Realität (VR) noch realistischer gestalten können. Ein bekanntes Problem in VR ist, dass virtuelle Objekte zwar echt aussehen, sich aber oft gewichtslos anfühlen. Man sieht einen schweren Hammer, aber man spürt sein Gewicht nicht, was die Immersion stört.

Unser Ziel ist es, dieses Problem zu lösen, indem wir zwei Arten von Feedback kombinieren:

- Visuelles Feedback: Was Sie in der VR-Brille sehen (z.B. die Größe eines Objekts).
- Haptisches Feedback: Was Sie fühlen. Hierfür nutzen wir eine Technik namens Elektrische Muskelstimulation (EMS), bei der sanfte elektrische Impulse Ihre Muskeln so aktivieren, dass ein Gefühl von Kraft oder Gewicht entsteht.

In der Studie werden Sie eine Hantel in der Hand halten. Während Sie dies tun, werden wir in der virtuellen Welt manchmal das Aussehen der Hantel verändern und/oder Ihnen

über EMS das Gefühl eines veränderten Gewichts geben. Wir möchten herausfinden, welche Kombination aus Sehen und Fühlen am überzeugendsten und realistischsten ist. Die Erkenntnisse dieser Studie sollen dazu beitragen, zukünftige VR-Anwendungen, von Trainingssimulationen bis hin zu Videospielen, immersiver und glaubwürdiger zu machen.

III. Versuchsaufbau

Die Versuchsanordnung setzt sich aus verschiedenen Geräten zusammen. Zur Erzeugung des haptischen Feedbacks dient das Stimulationssystem P24 Science (CE-zertifiziert) von Hasomed.

Die virtuelle Umgebung wird über eine VR-Brille (Meta Quest 3, CE-zertifiziert) dargestellt. Ein an einer physischen Hantel (3 kg) befestigter VR-Controller erfasst Ihre Armbewegungen in Echtzeit und überträgt sie in die virtuelle Welt. Ein Laptop (CE-zertifiziert) steuert den gesamten Versuchsablauf.

Zusätzlich verwenden wir verschiedene Messinstrumente (Umfangmessgerät, Messband, Handkraftmesser), um anthropometrische Daten (z.B. Armumfang, Greifkraft) zu erfassen, die für die Analyse relevant sind.

IV. Ablauf der Studie

Die Studie wird gemäß der nachfolgend beschriebenen Schritte ablaufen:

1) Persönliches Aufklärungsgespräch: Hier haben Sie die Möglichkeit, umfassende Rückfragen zu dieser Studie zu stellen und weitere Informationen zu erhalten, um Ihre Teilnahme zu verstehen.
2) Bedenkzeit und Entscheidung: Nach dem Gespräch erhalten Sie ausreichend Zeit, um über Ihre Teilnahme an der Studie nachzudenken und eine informierte Entscheidung zu treffen.
3) Einverständniserklärung: Bevor die Studie beginnt, werden Sie gebeten, ein Dokument zu unterschreiben, das bestätigt, dass Sie alles verstanden haben und freiwillig teilnehmen möchten.
4) Versuchsdurchführung:

    a) Ausfüllen eines Fragebogens zu körperlichen Eigenschaften und demographischen Daten: Hier werden wir Sie bitten, einen Fragebogen zu vervollständigen, der sich auf Aspekte Ihrer körperlichen Charakteristiken (Händigkeit, Gewicht, Körpergröße, Armlängen, Arm-, Taillen- und Hüftumfang, maximale Greifkraft) und Ihrer demographischen Daten (Alter, Geschlecht) konzentriert.

    b) Individuelle Kalibrierung der Stimulationsintensität: Die Stärke des elektrischen Stroms, der nötig ist, um einen Muskel zu aktivieren, ist bei jedem Menschen unterschiedlich. Daher beginnen wir damit, an zwei Muskeln Ihres Arms (Trizeps und Unterarm-Extensor) einen für Sie angenehmen und wirksamen Stimulationsbereich zu

ermitteln. Sie bestimmen dabei selbst die Obergrenze, indem Sie "Stopp" sagen, bevor es unangenehm wird.

c) Hauptteil der Untersuchung: Im Hauptteil der Studie werden Sie gebeten, die Hantel anzuheben und auf einer bestimmten Höhe ruhig zu halten. Während Sie die Hantel halten, wird ein kurzes, 10-sekündiges Ereignis ausgelöst. In diesem Ereignis kann sich das Aussehen der virtuellen Hantel verändern, Sie können eine Veränderung des gefühlten Gewichts durch die EMS spüren, oder beides gleichzeitig. Nach jedem dieser Ereignisse werden Sie gebeten, Ihre Wahrnehmung und Ihr Erleben anhand einiger kurzer Fragebögen zu bewerten. Dieser Vorgang wird für vier verschiedene Szenarien wiederholt, deren Reihenfolge zufällig festgelegt wird.

V. Risiken

Die Teilnahme an dieser Studie ist mit gewissen Risiken verbunden, die im Zusammenhang mit der Anwendung von Elektromuskelstimulation (EMS) stehen oder mit dem Versuchsaufbau verknüpft sind. Dennoch sind die Risiken der EMS sehr gering und treten nur bei äußerst hoher Intensität und langer Dauer der Stimulation auf:

Sehr selten kann es zu Hautirritationen kommen, vor allem wenn eine äußerst hohe Intensität und lange Dauer der EMS-Stimulation eingesetzt wird.

Ebenso selten können Hautrötungen auftreten, vor allem bei Verwendung von sehr hohen Stimulationsintensitäten über eine längere Zeit.

Wie nach intensiver körperlicher Aktivität kann es durch die Stimulation der Muskulatur zu Muskelkater kommen. Dies ist eine normale Reaktion des Körpers auf ungewohnte oder intensive Belastung.

Bitte beachten Sie, dass diese Nebenwirkungen in der Regel nur vorübergehend sind und nach Beendigung der Stimulation abklingen.

Für die weiteren in der Studie verwendeten Geräte, wie im Abschnitt "Versuchsaufbau" beschrieben, sind keine spezifischen Risiken bekannt.

Es besteht kein COVID-19-Infektionsrisiko, was über ein im Alltag zu erwartendes Maß hinausgeht.

VI. Versuchspersonen

Wir planen, 36 Versuchspersonen im Alter zwischen 18 und 64 Jahren für die Teilnahme an der Studie zu gewinnen. Die Anzahl der Versuchspersonen ergibt sich aus der statistischen Stichprobengrößenplanung. Für Ihre Teilnahme an der Studie, die voraussichtlich etwa 60 Minuten in Anspruch nehmen wird, erhalten Sie eine Aufwandsentschädigung von 15€. Die Vergütung efolgt am Ende der Studie. Die Studie wird vom IAW der RWTH Aachen mit der Auftragsnummer 4301001933 finanziert. Die Rekrutierung der Versuchspersonen für diese Studie erfolgt hauptsächlich durch das Anbringen von Informationszetteln in unserem Institut sowie an geeigneten Orten innerhalb der Universität.

1. Einschlusskriterien

Versuchspersonen können an dieser Studie teilnehmen, sofern sie die folgenden Kriterien erfüllen:

- Sie sind mindestens 18 Jahre und maximal 64 Jahre alt.
- Sie sprechen Deutsch auf einem kommunikationsfähigen Niveau (mindestens B2).

2. Ausschlußkriterien

Die Teilnahme an der Studie setzt voraus, dass **keine** der folgenden Bedingungen vorliegt:

- Schwangerschaft
- Vorhandensein von Herz- oder anderen Schrittmachergeräten
- Verdachtsfälle oder diagnostizierte Herzprobleme
- Frische Naben, Wunden, Inflammation, Hauterkrankung, Krebsläsionen an der Stelle der Stimulation
- Epileptische Anfälle

3. Risiko-/Nutzenbewertung

Die Entscheidung zur Teilnahme an dieser Studie sollte auf einer sorgfältigen Abwägung der potenziellen Risiken und Vorteile basieren. Wie bei jeder Studie, birgt auch diese bestimmte Risiken, die bereits dargelegt wurden. Dazu gehören Hautirritationen und Hautrötungen, die sehr selten auftreten und nur bei äußerst hoher Intensität und Dauer der Elektromuskelstimulation (EMS) beobachtet werden können.

Die potenziellen Vorteile der Teilnahme an dieser Studie hängen stark von den individuellen Umständen ab. Für viele Teilnehmer kann die Teilnahme an dieser Studie eine Möglichkeit bieten, einen Beitrag zur Forschung und zur Verbesserung des Verständnisses der Auswirkungen von EMS auf die Wahrnehmung von Gewicht und Kraft zu leisten. Darüber hinaus können Teilnehmer durch ihre Beteiligung ein besseres Verständnis für ihre körperliche Leistungsfähigkeit und ihre Reaktion auf EMS erlangen.

Es ist wichtig zu betonen, dass diese Studie in erster Linie wissenschaftlichen Zwecken dient und somit den Probanden nur geringe direkte Vorteile bietet, die Ergebnisse jedoch einen hohen gesamtgesellschaftlichen Mehrwert darstellen und in Zukunft einen wichtigen Beitrag zur Behandlung von Krankheiten oder zur Verbesserung der körperlichen Leistungsfähigkeit liefern.

VII. Versicherung

Die Studienverantwortlichen sind haftpflichtversichert für den Fall, dass Sie durch deren Verschulden einen Schaden erleiden. Unverschuldete Gesundheitsschäden, die während oder im Zusammenhang mit der Studie entstehen, sind über diese Betriebshaftpflichtversicherung nicht versichert.

Ein Versicherungsschutz in Form von Probandenversicherung oder Wege-Unfall-Versicherung besteht nicht. Sie sind während der Studie also nicht über das Institut für Arbeitswissenschaft durch gegen Sie verursachte Schäden versichert.

VIII. Freiwilligkeit der Teilnahme

Ihre Teilnahme an dieser Studie ist freiwillig. Sie können jederzeit ohne Angabe von Gründen die Teilnahme beenden. Dadurch entstehen Ihnen keine Nachteile.

IX. Informationen zum Datenschutz

Ihre personenbezogenen Daten werden ausschließlich von den an der Studie beteiligten Mitarbeitern des Studienzentrums verarbeitet. Diese sind zur Wahrung der Vertraulichkeit verpflichtet.

Im Rahmen der Studie werden Ihre Daten (siehe Abschnitt IV.) anonymisiert aufgezeichnet. Dies bewirkt, dass diejenigen, die (im Forschungszusammenhang) Daten verarbeiten oder einsehen, diese nicht Ihnen als Person zuordnen können. Damit ist es unmöglich die Studiendaten weiterhin individuell zuzuordnen.

Die im Rahmen der Studie erhobenen Daten werden von einem elektronischen Datensystem erfasst und statistisch ausgewertet. Nach Beendigung der Studie werden alle Daten nach den derzeit gültigen Richtlinien entsprechend gespeichert und archiviert. Die Verantwortung für die Einhaltung des Datenschutzes im Rahmen des elektronischen Datensystems liegt bei dem Institut und Lehrstuhl für Arbeitswissenschaft der RWTH Aachen, Eilfschornsteinstraße 18, 52062 Aachen.

Die Bearbeitung der erhobenen Daten erfolgt in Verantwortung von Prof. Dr.-Ing. Dr. rer. medic. Dipl.-Inform. Alexander Mertens, Abteilungsleitung, Institut und Lehrstuhl für Arbeitswissenschaft, Eilfschornsteinstraße 18, 52062 Aachen. Sie haben das Recht, Einsicht in Ihre Daten zu nehmen, die während der Studie erhoben werden.

Sollten Sie dabei Fehler in Ihren Daten feststellen, so haben Sie das Recht, diese korrigieren zu lassen. Weiterhin haben Sie das Recht auf Auskunft und Überlassung einer Kopie Ihrer Daten. Sie haben darüber hinaus das Recht sich bei einer Aufsichtsbehörde (siehe unten Punkt „Datenschutzaufsichtsbehörde“) über den Umgang mit Ihren Daten zu beschweren.

Die anonymisierten Daten werden dem Auftraggeber der Studie oder einer von diesem beauftragten Stelle zu wissenschaftlichen Zwecken zur Verfügung gestellt. Die Weitergabe der anonymisierten Daten erfolgt im Falle eines Antrags auf Zulassung weiterhin auch an den Antragsteller. Auch bei der Übergabe von anonymisierten Daten an einen Nicht-EU-Mitgliedstaat, z.B. für die internationale Vorlage bei den entsprechenden Behörden, werden Ihre personenbezogenen Daten vertraulich behandelt.

Adressen und Kontakte

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Datenschutzbeauftragter des Prüfzentrums:

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Datenschutzaufsichtsbehörde (Studienleitung):

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E-Mail: poststelle@ldi.nrw.de

Verantwortlicher für die Verarbeitung Ihrer Daten:

Prof. Dr.-Ing. Dr. rer. medic. Dipl.-Inform. Alexander Mertens
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X. Einwilligungserklärung

Titel der Studie: Untersuchung von visuohaptischem Feedback zur Gewichtswahrnehmung in der Virtuellen Realität

Name der Versuchsperson in Druckbuchstaben:……...

- Ich bin von Herrn / Frau _____ über Wesen, Bedeutung und Tragweite der Studie sowie die sich für mich daraus ergebenden Anforderungen aufgeklärt worden. Ich habe darüber hinaus den Text der Probandeninformation und dieser Einwilligungserklärung gelesen.
- Ich hatte ausreichend Zeit, Fragen zu stellen und mich zu entscheiden. Aufgetretene Fragen wurden mir vom Studienleiter beantwortet.
- Ich weiß, dass ich meine freiwillige Mitwirkung jederzeit beenden kann, ohne dass mir daraus Nachteile entstehen.
- Keine der Ausschlusskriterien liegt bei mir vor.

Ich erkläre mich bereit, an der Studie teilzunehmen.

Datenschutzerklärung

1. Ich willige ein, dass personenbezogene Daten über mich, insbesondere diese in Kapitel „Informationen zum Datenschutz“, wie in der Informationsschrift beschrieben erhoben und in Papierform sowie auf elektronischen Datenträgern beim Institut für die Arbeitswissenschaft aufgezeichnet werden.

Soweit erforderlich, dürfen die erhobenen Daten anonymisiert weitergegeben werden:

a) an M.Sc. Apostolos Vrontos oder von diesem beauftragte Stellen zum Zweck der wissenschaftlichen Auswertung,
b) im Falle unerwünschter Ereignisse: an das Bundesministerium für Bildung und Forschung, an die jeweils zuständige Ethikkommission und zuständige Behörden sowie von dieser an die Europäische Datenbank.

2. Ich bin darüber aufgeklärt worden, dass ich meine Einwilligung jederzeit widerrufen kann. Im Falle des Widerrufs werden keine weiteren Daten mehr erhoben. Ich kann in diesem Fall die Löschung der Daten verlangen.

3. Ich willige ein, dass die Daten nach Beendigung oder Abbruch der Studie mindestens 3 Jahre aufbewahrt werden.

Ich willige in die Verarbeitung der genannten Daten ein.

Ein Exemplar der Probandeninformation und der Einwilligungserklärung habe ich erhalten. Ein Exemplar verbleibt im Prüfzentrum.

_____ _____

(Datum & Unterschrift der Versuchsperson) (Prüfer Unterschrift)

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