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RESEARCH ARTICLE

Enhancing Hand Interactions and Accessibility in Virtual Reality Environments for Users With Motor Disabilities: A Practical Case Study on VR-Shopping

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ABSTRACT Over the past decade, Virtual Reality (VR) has achieved significant advancements in both quality and accessibility of its devices, particularly with VR headsets that offer an enhanced immersive experience at a reduced cost. This improvement is not only in graphical fidelity but also in interactivity within virtual environments, highlighted by advancements in tracking systems that allow direct manipulation with hands-free of external devices. However, these technologies are not fully adapted for use by individuals with motor disabilities in their arms and hands. This study addresses the ethical and moral obligation to make VR accessible to all users by proposing specific adaptations to the manual interaction mechanisms. Focusing on VR e-commerce as a use case, which is anticipated to revolutionize the shopping experience in the coming years, this study explores a scenario where users need to navigate and manipulate virtual products to examine and make purchase decisions. The experimental phase was conducted in a real-world setting at the Hospital Nacional de Parapléjicos in Toledo (HNPT), involving patients with spinal cord injuries and motor limitations. The results demonstrate that the adapted interactions not only enable users to perform tasks that are impossible with conventional mechanisms but also reduce the time and effort required to complete these tasks. Specifically, completion times achieved by users increased up to 91.6%. Also, the number of tasks completed highly increased in comparison with unadapted interactions. We elaborate an Effort Degree (ED) formula with various data items based on hand movements, that demonstrated that adapted interactions

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required around 40% less effort for individuals with mobility issues. These findings underscore the potential of adapted VR technologies to significantly enhance the inclusivity and utility of emerging e-commerce platforms, providing equitable access to new forms of digital engagement.

INDEX TERMS Virtual reality, adapted hand interaction, motor limitations, accessibility, inclusivity, e-commerce.

I. INTRODUCTION

Virtual Reality (VR) has experienced significant growth over the past five years due to various factors. A key driver has been the strong commitment from major technology companies such as META, Apple, Microsoft, HTC, Sony, and Samsung (among others). These companies have contributed to the evolution of VR by developing higher quality VR headset models (improving resolution, refresh rate, ergonomics, etc.) at a cost that is becoming affordable to a broader segment of society. This affordability could lead to VR and Extended Reality (XR) headsets becoming the next widely used devices, potentially reaching the level of mobile phone usage.

This momentum has contributed to a growing interest in this technology from numerous companies [32] and the developer community, thereby expanding the range and catalogue of products related to immersive spaces and motivating the emergence of the Metaverse [37]. Simultaneously, there is an increased interest within the scientific community, with a rise in research focused on areas such as Education [5], Health [38], Simulation [1], Entertainment [25], and E-commerce [2], among others. Notably, in the field of health rehabilitation, the use of VR is increasingly employed to provide users with controlled and gamified environments that enhance patient motivation and complement traditional therapies [10], resulting in positive effects on mobility recovery. Additionally, in e-commerce, VR is expected to drive a new evolution in the way we shop, offering experiences similar to those in a physical store but from the comfort of home [3].

In addition to technological advancements in hardware and the availability of software proposals, the growing interest is also driven by improvements in the interaction between users and virtual elements within the virtual space, resulting in a significant enhancement of the sense of immersion. This is mainly due to improved hand interaction without the use of external devices such as joysticks, or any other kind of controllers. Devices like the META Quest models integrate a set of external cameras in the headset itself and tracking algorithms that enable precise hand tracking and virtual representation [29]. The increased computational capacity of these devices, integrated into a smaller form factor, allows the execution of these demanding algorithms. Additionally, the API associated with the headset facilitates developers in implementing functionality related to hand and virtual component interactions. This is complemented by the physics engine included in the development environment (such as Unity), which endows objects with realistic behaviour.

Despite all these improvements, current hand interaction in immersive spaces requires good health, normal mobility in hands and fingers, and the ability to perform recognizable gestures [4]. Otherwise, most systems face significant difficulties in detecting user intentions within the virtual space [13]. Therefore, this excludes individuals with hemiplegia and motor limitations, who have difficulty moving their hands and fingers or suffer from spasticity. For example, those who have suffered a stroke or a spinal cord injury affecting their upper limbs, and do not have total disability in their hands. Hence, there is a need to adapt some of the basic hand interactions for individuals with such disabilities to create more accessible virtual environments for everyone.

As previously mentioned, VR has seen a significant boost in recent years, entering a phase of maturation. When a technology reaches this stage, broader concerns such as usability and, importantly, accessibility must be considered. Just as there is a global effort to improve accessibility in the real world, virtual environments must not be an exception. In fact, this is a fundamental requirement for VR/AR devices to be used widely on a global scale. Moreover, it is a moral imperative to make technological advances accessible to all.

In this article, we present a set of basic hand interactions in virtual spaces and their potential adaptations to make them more accessible for individuals with upper limb motor limitations. As a case study, we propose their use in VR-Shopping, a virtual shopping space where real products, previously digitized, are displayed. In this environment, users can explore the environment, navigate, and interact with products using their hands.

For the experimentation, we collaborated with the Hospital Nacional de Parapléjicos (HNPT) in Toledo, Spain, specifically with clinical and technical staff from the hospital's Biomechanics Unit and patients with Spinal Cord Injury (SCI) who suffer from motor limitations. All participants in the experiment were assigned a series of tasks within the immersive shopping space, which they had to complete using both non-adapted and subsequently adapted hand interactions. The results demonstrate that the use of adapted interactions allows people with SCI to fully complete not only the tasks designed for the case study but also to complete them in much less time. In addition, the effort made was also substantially reduced thanks to the adaptation made to the interactions, so muscular fatigue is alleviated.

This proposal has the potential to benefit a significant number of people globally. According to the World Health Organization (WHO),[1] it is estimated that over 1 billion people globally live with some form of disability, with a significant portion experiencing motor impairments.

[1]https://www.who.int/publications/i/item/9789241564182

Specifically, it is reported that approximately 2-3% of the global population, or roughly 150-225 million people, have motor limitations affecting their hands. These individuals could greatly benefit from the proposed adaptations in virtual hand interactions, enhancing their ability to engage with immersive virtual environments and participate more fully in activities such as VR-Shopping.

The remainder of the article is organised as follows. Section II presents related work on the need to adapt hand interactions for virtual reality applications and the commercial context by different VR headset manufacturers. Section III details the VR interactions that were adapted, as well as how they were adapted for people with SCI. Next, Section IV describes the case study carried out, including the methodology followed and the research questions. Following it, V shows both quantitative and qualitative analysis of the case study described previously. Finally, Section VI presents the conclusion of our work, summarising it and briefly describing our future work.

II. RELATED WORK

In this section, we discuss some significant contributions in the scientific-academic and commercial sectors related to interaction mechanisms and accessibility improvement in semi-immersive and immersive environments for individuals with disabilities. Specifically, in the scientific-academic context, we categorise the noteworthy research into four groups: i) studies that express and justify the need to enhance accessibility in VR (Virtual Reality) and AR (Augmented Reality) environments. Once this need is established, ii) other authors focus their efforts on assessing the current state of accessibility to raise awareness. iii) Subsequently, based on the measured accessibility levels, proposals aimed at enhancing it. iv) Finally, some studies involve hand interaction in VR environments among individuals with disabilities.

A. SCIENTIFIC-ACADEMIC CONTEXT

Recent studies have analysed the current shortcomings in terms of accessibility in systems based on VR and AR, highlighting the need to propose solutions for creating more inclusive virtual spaces. An example is the work conducted by [13], where the need to improve accessibility in both VR and AR systems for various types of disabilities is identified and justified. This article meticulously examines proposals to date for this purpose, in both the academic and commercial spheres. Among the proposals related to hand usage, there are none that suggest adapting interactions; instead, alternative methods such as the use of gloves or joysticks, which are unsuitable for people with hand deformities, or the use of voice commands, or issuing orders through pupil or head movement are discussed.

Following the same line of work, namely the detection of adaptation needs in interactions for accessibility improvement, [4] addresses the need to enhance accessibility in VR and AR environments for people with diverse abilities. It proposes using user model-based customization to tailor these technologies to individual needs, highlighting the limited research and application outside of gaming and navigation contexts. Through a workshop that brings together experts and developers, the paper explores new AR/VR applications and services, in addition to promoting the development of standards and guidelines to expand access and inclusion of these technologies in various social and educational settings.

[31] presents an exploration of the accessibility of VR systems for people with limited mobility. Through semi-structured interviews with 16 participants, the authors identified seven barriers related to the physical accessibility of VR devices, ranging from the initial setup of the system to keeping the VR controllers within the field of view of the cameras integrated into the VR headsets. Additionally, possible improvements were proposed to address some accessibility concerns, emphasizing the importance of considering the abilities of people with limited mobility when designing VR systems, as the capabilities of many participants did not match the design assumptions of current systems. For individuals with motor limitations in arms and hands it suggests interactions through voice commands and gaze control. In addition to the three previous studies, other authors such as [9], [12], and [30] complement what was mentioned above, following the same line of work.

Having highlighted the importance of constructing more immersive virtual environments, it makes sense to have the ability to measure the current state of accessibility in any system. Thus, there are studies aimed at measuring and evaluating the user experience in a VR environment, which subsequently allows for improvements to that experience. Such is the case with [28], which presents a model to assess and enhance the user experience in VR environments, focusing on hand movements and considering laterality (dominant and non-dominant hand). The study includes a practical case with two groups of users performing specific tasks, evaluating aspects such as engagement, enjoyment, and usability. The results indicate that customizing and adapting virtual environments according to laterality and individual responses significantly improves the user experience, suggesting the need for further research to optimize interaction and maximize usability and enjoyment in virtual reality contexts.

A second study that conducts an accessibility analysis in VR environments is [41]. This work aims to evaluate the effectiveness of accessibility features in a VR environment. An open-source solution called Gear VRF Accessibility was tested, which provides a framework for developers to adapt functions such as Zoom, Inverted Colours, Auto Reading (Screen Reader), and Subtitles in a VR environment. These features were implemented in an application and evaluated in a controlled environment with 12 participants with disabilities. The study concluded that while users appreciated the accessibility of the solution, there are still challenges in using VR without tactile contact, and further studies are needed to improve accessibility in various contexts and for different types of disabilities.

Given the importance of creating inclusive spaces, and the availability of mechanisms to measure the degree of accessibility, it makes sense to propose solutions to improve accessibility. [8] addresses the optimization of the placement of interactable elements in VR environments. This approach focuses on modifying the layout of interface elements to adapt them to the specific conditions of each user using manual interaction techniques, such as direct touches and air gestures. However, the study does not specifically address the needs of users with motor limitations, which implies that the proposed adaptations might not be fully accessible to people with such limitations.

Other authors, like [17], rely on VR-based systems to complement rehabilitation methods for patients with motor limitations, particularly patients with spinal cord injuries who require upper limb rehabilitation. They propose an advanced calibration method that individually detects limitations on the left and right sides of the body. Based on this information, the location of objects with which the user must interact is automatically adjusted to make them accessible and to ensure they do not require excessive effort or compensations that could further endanger the patient.

Moreover, we want to show use cases where accessibility has been improved, particularly through the use of hands as the primary mechanism of interaction. Reference [35] propose an intelligent wheelchair control system that operates solely through hand use instead of joysticks for people suffering from dystonia. The method is primarily based on a recurrent neural network. It includes a camera integrated into the wheelchair and vision algorithms that recognize different hand poses with motor limitations and translate them into commands. It is designed for patients who cannot use joysticks. This is not implemented in an immersive environment, but rather with a 3D simulator displayed on a 2D screen. It starts from pre-recorded poses, but each patient is a different case. They look for similarities with reference poses. Tested with three patients. Other similar articles, in which gesture recognition is used for wheelchair control, include [11] and [19].

Reference [26] discusses how traditional user interfaces in virtual reality (VR), which are vision-centred, do not sufficiently consider the effectiveness and comfort of manual interactions. In response, an adaptive hand movement user interface technique is proposed to improve the performance of manual interactions in VR. Through an experiment with 24 participants, it was demonstrated that the choice of hand and position of the interaction significantly influence the efficiency and accuracy of target selection. The results indicated that adaptive hand interaction results in greater interaction efficiency and less physical effort and perceived difficulty of the task compared to the traditional vision-centred interface. Guidelines are provided for designing more efficient and user-friendly user interfaces in VR applications. All is based on the position of the hand relative to the chest, with no gestures involved.

Herrera et al. [18] proposed a serious games platform based on VR for the rehabilitation of upper limbs in patients with motor limitations who have suffered a stroke or spinal cord injury. The platform features a core common to all serious games, with basic functionality. Part of this functionality is focused on hand tracking and the adaptation of hand interaction mechanisms to manipulate virtual objects. The adaptation primarily centres on modifying pinch grips for individuals who are unable to perform the complete gesture of touching the thumb and index finger together.

We conclude this section by focusing on how the difficulty faced and effort made by participants in case studies involving the use of VR applications has been measured. In this sense, we will not limit ourselves to case studies whose volunteers have limited upper limb motor skills in order to cover a broader spectrum of participants. Reference [15] focuses on evaluating the interaction modalities of hand-tracking and handheld controllers in virtual reality learning environments (VRLEs) for performing motor tasks such as reach-pick-place activities. Quantitatively, in-game analytics were utilised to measure performance metrics such as task duration, frequency of clicks (right and left), and the number of objects picked. These metrics were systematically recorded across four experimental conditions (hand-tracking vs. controller × photorealistic vs. non-photorealistic environments) to capture detailed behavioural data during task execution. Qualitatively, the study implemented the Rated Scale Mental Effort (RSME) questionnaire to evaluate the perceived mental workload of participants. After completing each task, participants provided subjective feedback using this scale, which allowed researchers to gauge their cognitive and physical effort.

Jamalian et al. [21] evaluated user effort and difficulty during a memory puzzle task relied on a detailed collection of performance data. To assess the accuracy of task execution, the researchers measured the percentage of trials where participants correctly replicated both the order and sequence of the patterns (referred to as "Correct Order and Pattern"). A related metric, "Correct Pattern Only", captured instances where participants reproduced the correct pattern without maintaining the proper sequence, providing an additional layer of insight into user performance. Timing metrics were also central to the study. The "First Selection Time" recorded the time elapsed before participants selected the first button in a trial, serving as an indicator of their response immediacy. Additionally, the "Trial Completion Time" measured the total duration required to complete each trial, offering a quantitative view of task efficiency. To evaluate motor behaviour and interaction dynamics, the study tracked the usage of participants' dominant and non-dominant hands using hand-tracking data. By calculating the percentage of interactions performed by each hand, the researchers investigated whether the naturalistic interaction of hand-tracking encouraged more balanced hand usage compared to controller-based systems.

The work of [27] researched the usability of hand-tracking for grab-and-place tasks in immersive virtual reality employed a detailed set of metrics to evaluate the effort and difficulty associated with this interaction method. Performance data from hand-tracking interactions were central to the analysis, focusing on accuracy, task timing, and error rates. Accuracy was measured as the Euclidean distance between the virtual object's placement and the target location, providing a precise indicator of interaction precision. Timing metrics included the duration from when the object appeared to when it was successfully grabbed, referred to as grab time, and the time from grabbing to placing the object, termed release time. These measurements highlighted the efficiency and responsiveness of the hand-tracking interface. Total task time, which encompassed the entire interaction from the object's appearance to its placement, further contextualized the interaction's overall efficiency. Accidental drops, defined as unintentional releases of objects before placement, were recorded to identify errors specific to the hand-tracking modality and assess its reliability under experimental conditions. Subjective measures complemented these performance metrics, capturing user perceptions of the interaction. Participants rated their experiences using the System Usability Scale (SUS), evaluated the naturalness and precision of hand-tracking, and reported their sense of agency—how much they felt in control of their virtual hands. These qualitative responses added depth to the analysis by reflecting the cognitive and physical demands experienced during hand-tracking use.

The authors of [20] assessed fine motor skills, specifically focusing on reaching accuracy under various sensory and cognitive conditions. Hand-tracking data were central to evaluating effort and difficulty in the tasks performed by healthy participants and individuals with cerebellar stroke. Metrics included the accuracy of reaching movements, measured as the angular difference between the target location and the participant's finger trajectory. This provided a precise indicator of task performance. Additionally, the study recorded reaching precision, calculated as the standard deviation of endpoint accuracy across trials. Reaching time, defined as the duration from the appearance of the target to the completion of the movement, was also measured to provide insights into the speed and control of hand movements. These metrics allowed for a detailed analysis of the interplay between sensory modalities, such as vision and proprioception, and their impact on motor task execution. Hand-tracking data specifically enabled the evaluation of performance under conditions where visual feedback of the hand was manipulated or absent, isolating the reliance on proprioceptive input.

B. COMMERCIAL ENVIRONMENT

In this section, we will explore accessibility features included in current VR headsets of the market per manufacturer. META - accessibility features https://www.meta.com/es-es/help/quest/articles/in-vr-experiences/oculus-features/accessibility-features/, allow for height adjustment, audio balance, colour correction, contrast, subtitles, mono audio, joystick control remapping, font size adjustment, and thumb calibration for joystick handling. There is no adaptation for hand interaction.

HTC https://www.htc.com/us/accessibility/ - HTC virtual reality headsets offer various accessibility settings to enhance the experience for users with disabilities. These settings include options to improve visibility such as the TalkBack screen reader, which allows users to navigate and receive auditory feedback without needing to look at the screen. Font sizes can also be adjusted and magnification gestures can be enabled to enlarge parts of the screen. For those with visual impairments, options such as color inversion and color correction for different types of color visual impairment are available. In terms of hearing, HTC devices offer compatibility with hearing aids and special modes that reduce interference, as well as options for closed captions and visual or vibration notifications. The devices are also equipped for voice input and voice commands to facilitate interaction without the need to touch the device, and functions can be accessed through the use of external switches or device buttons. Additionally, features like motion gestures and touch delay adjustments help improve interaction for people with manual dexterity difficulties.

Sony https://www.playstation.com/en-us/ps-vr/ - Concerning the accessibility configurations for the PlayStation VR2, it is important to note that all of the PlayStation 5's system-level accessibility settings, with the exception of Zoom, remain available when operating in virtual reality mode. This encompasses support at the system level for functionalities such as Colour Correction, Invert Colour, and Custom Button Assignment.

HP https://support.hp.com/us-en/product/setup-user-guides/hp-reverb-g2-virtual -reality-headset/33835976 - The main configuration options that primarily affect accessibility are found in Audio & Visual and, on the other hand, Display and Graphics.

Finally, Pico 4 https://www.picoxr.com/global - No official page was found that includes features or options to improve accessibility.

To conclude the section, it is worth mentioning that most of the cited works do not address the adaptation of hand interactions for people who do not have a total disability and can move them with limitations. As an alternative, they usually propose interaction with other parts of the body, such as the use of voice, head movements, or eye tracking. In fact, in [29], a review that includes 80 studies, it is found that voice interfaces are the most studied, followed by eye and head tracking. Other novel interfaces include brain control and facial expressions. Therefore, there is a need to improve and adapt hand interactions without the necessity of resorting to other parts of the body.

III. ADAPTED HAND INTERACTIONS FOR VR ENVIRONMENTS

In this section, we will present our proposal of adapted interaction mechanisms used in this case study. The prototype we based the following interactions on was developed for Meta Quest headsets. Consequently, we utilised the API and features provided by Meta's SDK version 59.9 to adapt such interactions. This choice was driven by Meta's position as a leading and successful company in the field of VR, alongside the extensive development and continuous updates of its API. Additionally, Meta devices feature hand tracking, enhancing the shopping experience by allowing users to use their hands, which, as demonstrated in Section II, is easier for individuals with upper limb motor difficulties compared to using controllers. Moreover, people without precise motor coordination cannot grab a controller and use the buttons, joystick or crosshead of it. In any case, the proposed adaptations are not dependent on a particular technology and are implementable on other VR headset models through their development API.

Furthermore, we would like to note that the adaptations were made with the aim of being as generic as possible. That is, whichever injury degree or upper limb part affected by such injury is, the adapted interaction should work for the user. In the following subsections, we will describe the interaction mechanisms with and without adaptions, highlighting the features included for its adaption. We have categorised the interactions mechanisms in the following categories: i) interaction with products, involving grasping and releasing products as well as adding or removing them to a shopping cart, ii) navigation, involving adapted teleportation and iii) virtual environment inspection, involving adapted rotation of the user's view.

A. VIRTUAL OBJECT GRASPING

In the context of VR applications, grasping or grabbing objects is a fundamental interaction mechanism that enables users to thoroughly explore them by rotating, scaling, or performing more complex actions, such as moving or detaching sub-parts. Like any other interaction implemented by Meta's API, grasping relies on the *Interactor-Interactable* framework. *Interactors* are added to input devices, in this case, the virtual hands—and *Interactables*, which are added to objects in the environment intended for interaction with the corresponding *Interactors*. This framework embedded in the Meta SDK allows these components to switch between four states: *Disabled*, *Normal*, *Hover* and *Select*. These states indicate whether a certain interaction defined by the Meta SDK can occur on a certain object configured as *interactable* for certain interaction.[2] Based on this, the interaction requires the hand to be near the object with the *Interactable component*

FIGURE 1. A set of screenshots showing the grab interaction: (A) approaching the hand near to a grab Interactable object (Hover state), (B) the virtual hand grabbing an object, along with the hand bones mapping, (C) performing a two hand grab and (D) scaling an object by using the two hand grab.

and other necessary elements, such as a *Collider*,[3] and to perform a *pinch* gesture grip or a palmar grip. The latter involves bringing the fingertips towards the palm. Grasping an object can be achieved using either the *pinch* grip, the palmar grip, or both. While the *pinch* is detected through an algorithm of the API, which takes into account grip strength and the fingers involved based on *hand-tracking* data and 3D coordinates, the palmar grip and its strength are based on the curl values of the fingers to determine if there is a grip.

To release a grasped object, certain distance thresholds values must be met for the API to recognise that the grip is no longer being performed. The distance values are calculated taking into account the 3D coordinates of the *Collider* bounds of the object and the 3D coordinates of the fingers used to grab the object. Generally, it is recommended to fully extend the fingers to facilitate this detection and release the grasped object.

1) BASE INTERACTION

Having described how to grasp and release an object, we will now illustrate an unadapted grasp. Figure 1.A shows a virtual hand of the user approaching an object to grasp it. Upon contacting the boundaries of its Collider, the user's hand lights up, providing visual feedback to indicate that performing a *pinch* or *palmar* gesture will grasp the object.

Furthermore, Figure 1.B illustrates the mapping of the hand bones onto the virtual hand grasping an object. A visual component rendering the hand's skeleton has been added to show that, even when performing a *pinch* gesture to grasp,

[2] More information in the official documentation: https://developer.oculus.com/documentation/unity/unity-isdk-interactor-interactable-lifecycle/.

[3] A component from the Unity's physics engine that defines a surrounding shape over the object to allow physics interactions. A component, in the context of Unity, can be comprised of configurable elements provided by the game engine, such as Colliders, Cameras or Materials, or C# scripts.

the API allows modifying the visual form of the hand to fit a specific shape, enhancing immersion This visual form must be recorded for the object.

Additionally, Figure 1.C and Figure 1.D demonstrate a two-handed grasp, which allows for scaling an object. While Figure 1.C shows that when grasping the ball, the grasp is indicated by the other hand lighting up in blue, Figure 1.D shows wireless earbuds being scaled using this grasp. Following this, we will show the adapted grab interactions.

2) ADAPTED INTERACTION

Grasping by pinching, which involves bringing the index finger and thumb together and exerting force, assumes neuromuscular integrity and fine coordination that may be severely compromised in individuals with SCI or those who have suffered a stroke. In patients with SCI, depending on the level and severity of the injury, there can be dysfunction of both upper and lower motor neurons, resulting in varying degrees of paralysis and spasticity. This affects the ability to perform precise movements, such as the pinching gesture, due to a loss of muscle strength, fine motor control, and coordination. Additionally, patients who have experienced a stroke often face additional challenges such as hemiparesis or hemiplegia, which results in weakness or paralysis on one side of the body, further complicating the ability to manipulate small objects and perform precise hand gestures. Moreover, some users might not be able to keep the object grabbed as the force exerted might not be the needed to maintain the grasp.

In order to address these limitations, object grasping has been modified using two different approaches: i) by adjusting Meta's API script and ii) through a C# script developed by the authors. The modification involves extending an interface to detect if a given finger is grabbing as well as scoring the strength of such pinch (see Algorithm 1). The function to get the score of the pinch grab can be further used with other finger joints to adapt other grabs such as palmar grab, or define a new one. This adaptation can assist individuals with limited finger mobility in performing grips through the movements they are capable of making, by not requiring them a full pinch. The float values assigned to the given parameters can potentially be identical across multiple parameters, streamlining the configuration process while maintaining functionality. These adaptations coexist, so that if a user with SCI can perform a grasp to some degree, i) will apply. However, if he/she cannot, due to proximity and time, the self-grasp ii) will be performed. In the absence of haptic gloves or any other tool that allows us to measure the force with sensors, Algorithm 1 allows to modify grab detection by relying on the inverse of the Euclidean distance between joint positions. A grab is detected when the computed strength exceeds the grab threshold G but remains below the maximum allowed threshold T. This ensures both proximity and validity for detecting the intention of grabbing an object. Those threshold values were set according the range of values managed by the Meta API and the help of HNPT therapists by looking how the values were mapped to joint positions when a pinch was being performed.

Algorithm 1 Detect Pinch Grab and Score Strength

Data: Vector3 position of Joint 1 *pos1*, Vector3 position of Joint 2 *pos2*, strength threshold *T*, grab threshold *G*
Result: Boolean indicating if a pinch grab is detected, strength of the pinch grab

function ScorePinchStrength(*pos1*, *pos2*)
    distance ← EuclideanDistance*pos1*, *pos2*
    Return $\frac{1}{distance}$
end function

function DetectPinchGrab(*pos1*, *pos2*, *T*, *G*)
    strength ← ScorePinchStrength*pos1*, *pos2*
    if $strength \geq G$ & $strength \leq T$ **then**
        isPinchGrab ← true
    else
        isPinchGrab ← false
    end if
    Return (*isPinchGrab*, *strength*)
end function

However, these modifications may not be feasible for individuals with significantly reduced hand mobility. Therefore, a developed script (see Algorithm 2) detects when the hand is over the surface of the object, and after one second, an automatic grip is performed. Although this may seem straightforward, the *Interactor-Interactable* lifecycle must be considered, requiring the states of the *Interactors* and *Interactables* to be checked to execute the automatic grip.

Automatic grasping with both hands does not happen independently in code; instead, it occurs simultaneously when both hands grasp the object automatically, following the *Interactor-Interactable* lifecycle. The algorithm makes use of specific functionalities of the Meta SDK, e.g. checking the state of the hand grab Interactor attached to hand H, forcing the grip or checking if the hand is hovering over an object. On the other hand, Update is a native function of the Unity engine that runs once per frame of the application, which allows us to execute a functionality throughout the execution of the application. Following this lifecycle ensures that functionalities like adapting the visual form of the virtual hand during a grip are retained, as shown in Fig. 2.B.

Figure 2.A displays the state of the hand before initiating a grip, highlighted by a blue outline, which is the same visual feedback in the unadapted interaction. Once the grip is performed, the outline turns green as shown in Figure 2.B. Meanwhile, Figure 2.C illustrates the distance grip implemented, based on *raycasting*. This ray is rendered with the LineRenderer component, which belongs to a Unity library. In addition, Unity's physics engine allows to detect

Algorithm 2 Auto-Grab of Grabbable Objects

Data: Required time to grab *r*, timers *t1* and *t2* that determine whether or not perform an automatic grab, object references that control the progressive rendering of the feedback circle *P1* and *P2*, Interactors *H1* and *H2* (representing left and right hand grab interactors), boolean that allows auto-grab *a*

Result: The grabbable object *O* is grabbed by one or both of the user's hand

function AutoGrabHandler(H,t,P,a,r)
    if a is true **then**
        if H is not grabbing **then**
            $a \leftarrow false$
        end if
    else
        if $HandIsHovering(H)$ **then**
            Set $P.pointing \leftarrow false$
            $t \leftarrow t + Time.deltaTime$
            if $t \geq r$ **then**
                $H.ForceSelect(H.Candidate, true)$
                $t \leftarrow 0$
                $a \leftarrow false$
            end if
        else
            $t \leftarrow 0$
        end if
    end if
end function
while Update is called **do**
    $AutoGrabHandler(H1, t1, P1, a1, r)$
    $AutoGrabHandler(H2, t2, P2, a2, r)$
end while

the collision of the ray with the objects marked as attractable to start the grabbing process at a distance. The ray originates from the carpometacarpal joint using the forward direction of the object, taking into account its current orientation in the world space. After pointing at an object for a second and a half at a certain minimum distance, beyond the reach of a stretched arm, the object will move towards the user's hand and perform a grip, as shown on the right side of Figure 2.D. The ray originates from the metacarpophalangeal (MCP) joint of the index finger.

Finally, we address the release of a grasped object. Our proposed solution involves pointing to an object within the virtual environment, which follows the user and maintains a fixed distance and orientation for easy location. In this case, we use the recycling bin metaphor to release the hand from the selected object. This solution allows users to release grasped objects more precisely, acknowledging that not all users can exert sufficient force with their fingers for the hand tracking system to recognise a released grip. The left image of Fig. 2.D shows the ray that, after pointing at the bin for one second, will release the object and it will automatically return to its original position.

FIGURE 2. A set of screenshots showing the adapted grab interaction: (A) auto-grab by approaching the hand near to a grab Interactable object (Hover state), (B) an object being grabbed (Select state) after one second has passed, (C) an user aiming with its right hand to perform a distant grab and (D) automatic release of objects by pointing to a bin.

B. VIRTUAL ENVIRONMENT NAVIGATION

Locomotion in VR environments has been and is of interest in the field of VR research. One of the main limitations to proposing navigation methods that do not involve physical movement of the user, i.e. physically moving around, is motion sickness. In large virtual spaces, it is difficult to have a physical space of the same dimensions, so the need arises to offer the user another form of locomotion. This can be through the movement of the joysticks of the controllers, which causes more motion sickness, or through teleportation, which causes hardly any motion sickness and is more enjoyable for the user than other techniques. These facts were demonstrated by Puritat et al. [34] in their case study of a large virtual space in a museum.

Therefore, teleportation is one of the most popular and frequently employed navigation methods in VR, offering a fast and convenient way to move within the environment while minimising motion sickness [36]. Despite this, teleportation can be very difficult to perform by potential users, who we intend to help with adapted hand interactions. Firstly, because the use of controllers may be too difficult for them, as they require a certain amount of upper limb mobility and hand shape in order to be able to use buttons or joysticks included. Secondly, developers of VR SDKs often define a default hand shape to invoke this interaction so as not to conflict with other interactions or gestures. This is why we have modified, in the case of the Meta SDK, the shape and the way of activating this interaction with the hands so that it can be accessible.

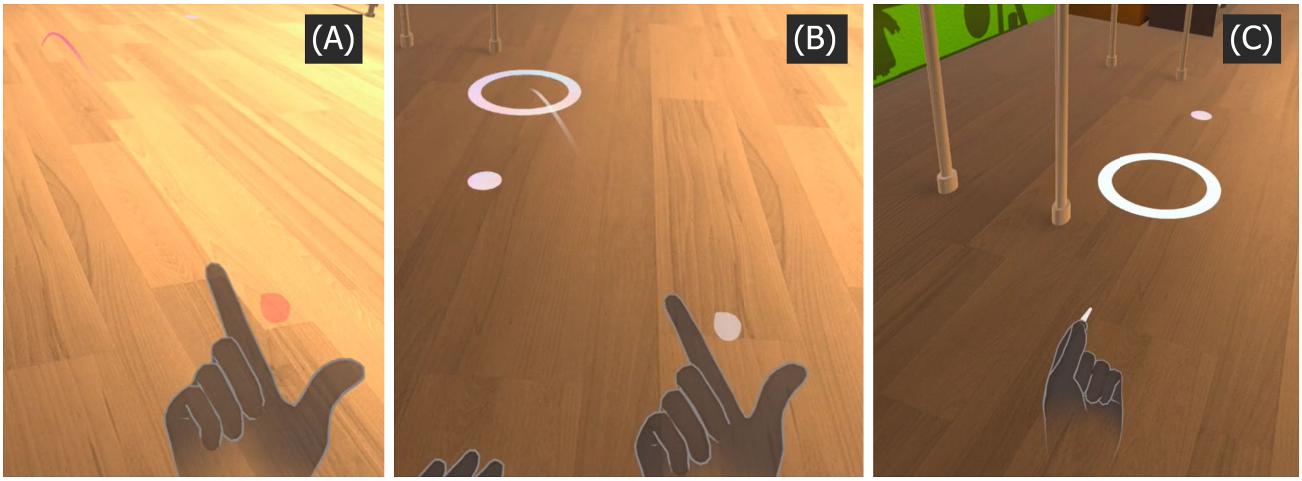

FIGURE 3. A set of screenshots showing the base teleportation interaction: (A) pointing to a place where teleportation is not allowed (Normal state), (B) pointing to a teleportation point, where teleportation is allowed (Hover state) and (C) performing the pinch gesture to activate the teleportation (Select state).

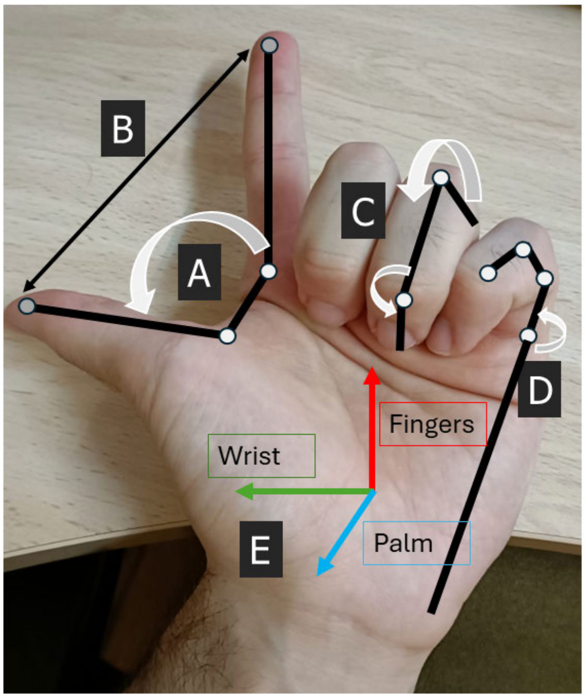

FIGURE 4. The L-shape with a left hand that enables the teleportation arc. The finger features of Meta's SDK are as following: (A) ***Abduction***, (B) ***Opposition***, (C) ***Curl*** and (D) ***Flexion***. (E) represents the world coordinate axes that allow transform recognition of the hand's position in 3D space.

1) BASE INTERACTION

To be able to perform a teleportation to some point in the virtual space, Meta's API requires the configuration of the relevant objects in the Unity scene with appropriate scripts, as well as the identification of a *hand pose*. The concept of *hand pose* is essential for adapting these component interactions:

- **Shape recognition**. This is based on a set of boolean conditions regarding the position of one or more fingers. When the data collected by *hand tracking* satisfies these conditions, the shape is "activated". The boolean conditions are derived from comparing the data obtained from *hand tracking* with defined *finger features*,[4] which specify finger positions to define a shape. These features include *curl*, *flexion*, *abduction*, and *opposition*. Thresholds are established to determine the transition from one feature to another.
- **Transform recognition**. The hand transform represents the orientation and position of the hand in a 3D space. This recognition is based on boolean conditions that must be met concerning the fingers, wrist, and/or palm. For instance, it can be verified that the palm is orientated upward or downward, or that the fingers or wrist are oriented upward, among other possibilities.

With regards **shape recognition**, Figure 4 shows the different finger features of the L-shape that are needed to invoke the teleportation arc. We provide a description of the used finger features for each finger and the values taken to detect this L-shape with the hand. For further information on other possible values and their meaning, please refer to the official documentation.

Figure 4.A shows *abduction*, which is the angle between two adjacent fingers, measured at the base of those two. In this case, it measures the angle between the thumb and its adjacent that is closer to the pinky, i.e., the index finger. In this case, the value taken is *Open* as the two fingers are spread apart. Figure 4.B illustrates *opposition*, described as how close a given fingertip is to the thumb tip. In this case, the value taken is *Near* which means that the fingertip joints are between 1.5 cm and 15 cm apart. Figure 4.C shows the curl performed

[4] https://developer.oculus.com/documentation/unity/unity-isdk-hand-pose-detection/#finger-features

with the ring finger, which quantifies how bent the top two joints, represented with white circles, are. In this case, the value taken is *closed*, which means that the fingers are tightly curled inwards with the tips almost touching the palm or doing it. Finally, Figure 4.D represents the *flexion*, which is the extent that the Proximal joint is bent relative to the palm. In this case, the value taken is *Closed* as the joint is fully bent, almost perpendicular to the palm.

Figure 3 illustrates the hand poses required to initiate a teleportation or rotation interaction. Figure 3.A shows the a hand making a shape similar to an L facing upwards, which invokes the arc that allows the user to aim where the user wants to teleport. However, the arc is shown in red as teleportation is not allowed where the user is aiming. Nevertheless, Figure 3.B shows that the colour changes to white, as well as the teleportation point aimed at is enlarged when it is pointed. Finally, Figure 3.C the action that activates teleportation when pointed to a place that allows teleportation, which involves making the *pinch* gesture.

2) ADAPTED INTERACTION

Meta's SDK offers an API that allowed us to use a single component of *transform recognition* (see Section III-B1) to activate the arc to point where the user wants to teleport.

The basic interaction defined for teleportation in a VR space using the L-shaped hand gesture, with the index and thumb fully extended, is unrealistic for patients with claw hand deformities. Therefore, it is necessary to find alternative solutions. In this case, we have decided that the user only needs to point to the desired teleportation site for one second and a half, as illustrated in Figure 5. In this case, the shape of the user's fingers is not considered; they only need to point the palm of the hand upward to invoke the arc. This allows for generic adaptation to a wide spectrum of injuries, as we removed the requirement of performing a concrete shape with the hand.

To avoid errors when pointing, the environment has been marked with small circles indicating teleport points. These points will cause the arc to snap to the indicated location, allowing for some aiming error rather than only allowing that single circle. This is achieved by providing the teleportation point a wider *Collider* area. We also added visual feedback in the form of a loading circle, which progresses until completion as the pointing time advances, preventing users from stopping too early and having to restart. When the circle is 100% complete, which means that the user has kept their hand in the same position for a certain amount of time, the user is then teleported to the chosen destination point. The following Google Drive link contains a video shows the adaptation interaction to teleportation as we have described it https://github.com/AIR-Research-Group-UCLM/VR-Hands-Interactions-Adapted/blob/master/video_link.txt.

The algorithm 3 shows the pseudocode of the Update function that controls whether to teleport or not a user to a given destination point based on pointing time over a certain teleportation point. The *Select* and *Unselect* events are manually sent in the code to not alter the *Interactor-Interactable* lifecycle, since the adaptation is based on time rather than on user inputs through hand-tracking detection.

Algorithm 3 Auto-Teleportation

Data: Boolean h: Indicates if the teleportation arc is hitting a teleportation point. Teleport Interactor *tpi*: Manages teleportation interactions. Timer t: Tracks hover time over a teleportation point. Time required for teleportation r: Hover time required for teleportation. Feedback manager *ipm*: Controls the visual feedback progression (circle). Boolean *wp*: Tracks if the teleportation arc was hitting a teleportation point in the previous frame.

Result: The user being teleported to a certain tp point that was aimed to over r seconds

while Update is called **do**
  if *tpi*.State is Active **then**
    if *tpi*.State is not Select and h = true **then**
      $t \leftarrow t + Time.DeltaTime$
      if $not wp$ **then**
        $ipm.SetPointing(true)$
        $wp \leftarrow true$
      end if
      if $t \geq r$ **then**
        $ipm.SetPointing(false)$
        $wp \leftarrow false$
        Send event of Select occurred
        $t \leftarrow 0$
      end if
    else
      $ipm.SetPointing(false)$
      Send event of Unselect occurred
      if wp **then**
        $wp \leftarrow false$
        $ipm.SetPointing(false)$
      end if
    end if
  end if
end while

C. VIRTUAL ENVIRONMENT INSPECTION

Another functionality we are adapting is body rotation in virtual spaces. This feature allows the user's view to be rotated by a specific angle relative to the vertical world axis of the scene, thereby simulating a turn without requiring physical rotation. Although this option may appear less essential for an person/people without disabilities, it is crucial for users who have experienced a stroke or other incidents that require the use of a wheelchair, as it facilitates the exploration of a virtual space 360 degrees.

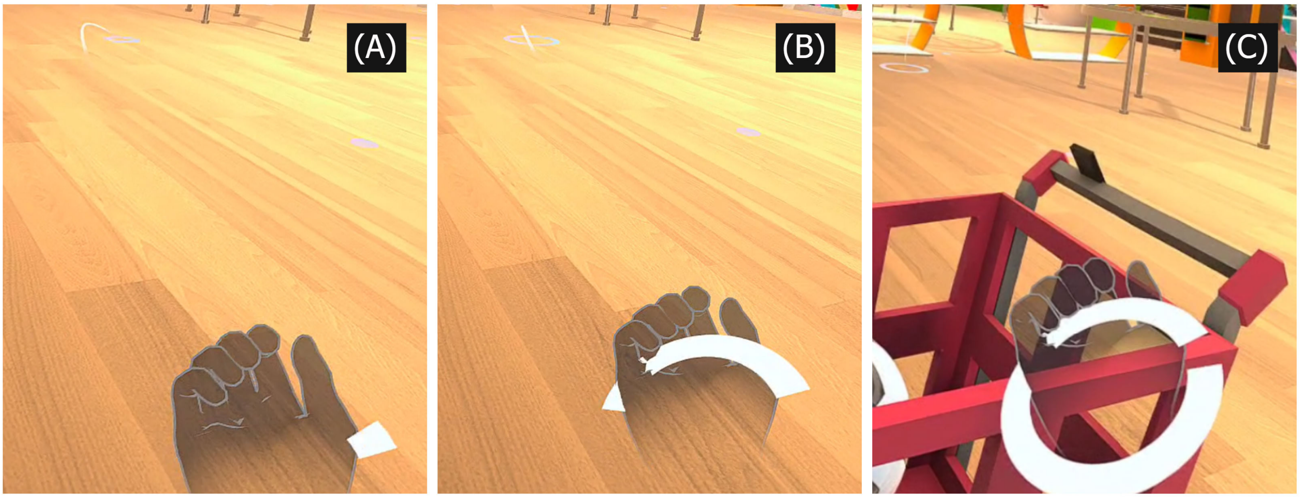

FIGURE 5. Screenshots that show the adapted teleportation interaction: (A) pose pointing to a place where teleportation is allowed (Normal state), (B) the adapted teleportation shows a circle that progressively fills as the user keeps pointing to the teleportation point and (C) shows the circle almost filled completely before teleporting the user.

1) BASE INTERACTION

The Meta SDK combines the invocation of two interactions, the teleportation we have shown in the previous section, and the rotation of the virtual body, depending on a certain condition. This combination is implemented with a series of scripts that are ultimately based on the concept of gates. Thus, when a condition is met on a given variable, the teleportation arc is invoked. If it is desired to invoke the virtual body rotation interaction, the user will modify these values by moving his hands, and this data is collected by the hand-tracking technology. These variables are a minimum and maximum degrees of wrist rotation angle, which determines which interaction should be invoked in order to be performed, as long as the hand shape that the hand-tracking checks these angles, i.e. the L-shape, has been detected.

In the case of the base interaction, the wrist must be rotated in order to make the palm of the hand point towards the ground. Once a certain angle of rotation is reached, arrows will be invoked that can be selected by the user to rotate 45 degrees with respect to the vertical axis in the direction marked by these arrows.

Therefore, Figure 6.A shows the arrows being invoked. The selection of rotation towards one direction or the other consists of performing the *pinch* gesture on one of the arrows.

2) ADAPTED INTERACTION

As we have already shown in Section III-B2, the restriction imposed by Meta's SDK of combining the wrist turning angle to determine whether to activate the teleportation arc or the rotation arrows, we have chosen to recognise the hand position with the palm facing upwards, avoiding the need to flex or extend the fingers. In the case of virtual body rotation, it still requires turning the wrist a certain amount of degrees to invoke either the left arrow (see Figure 6.B) or the right arrow (see Figure 6.C). However, we are aware that the minimum and maximum wrist rotation angles may vary depending on the user and his or her limitations, as well as the difficulty of performing the *pinch* to select to perform the interaction.

Therefore, we have implemented two features to avoid these problems. First, we have modified how to select the arrows. Instead of having to perform a *pinch* over them, the action required is moving the palm's face towards the direction of the arrow. This was achieved by i) implementing a **transform recognition** component that states the orientation of the wrist and the fingers as shown in Figure 4.E, without considering the shape, and ii) using a component of Meta's SDK that allows activating a state based on the rotation performed with a joint over a span of time. The second step used a joint named "Hand Start" that represents the wrist, and the minimum time to perform the rotation was set to 0.1 seconds. This allows for slow and faster movements.

While our first goal was to adapt the way the interaction was used, the second one focused on the invocation of the virtual elements that allow to perform teleportation and virtual head turning. Based on each user wrist mobility limitation, the invocation of the arrows and the teleport arc were adapted. Therefore, we develop a *script* that collects the minimum and maximum wrist rotation angle between 0 (palm face towards ceiling) and 180 (palm face towards floor) degrees. Algorithm 4 describes the logic behind this feature. This pseudocode heavily relies in the Vector3 class provided by the Unity engine, which represents a point in 3D world coordinates of the application. In order to provide further explanation on the variables used, a brief description of them is provided. While *minAngle* and *maxAngle* represent the range of angles that can be detected from wrist rotation to invoke the arrows or teleportation arc, *wrist.angle* represents the current rotation's angle of the wrist,

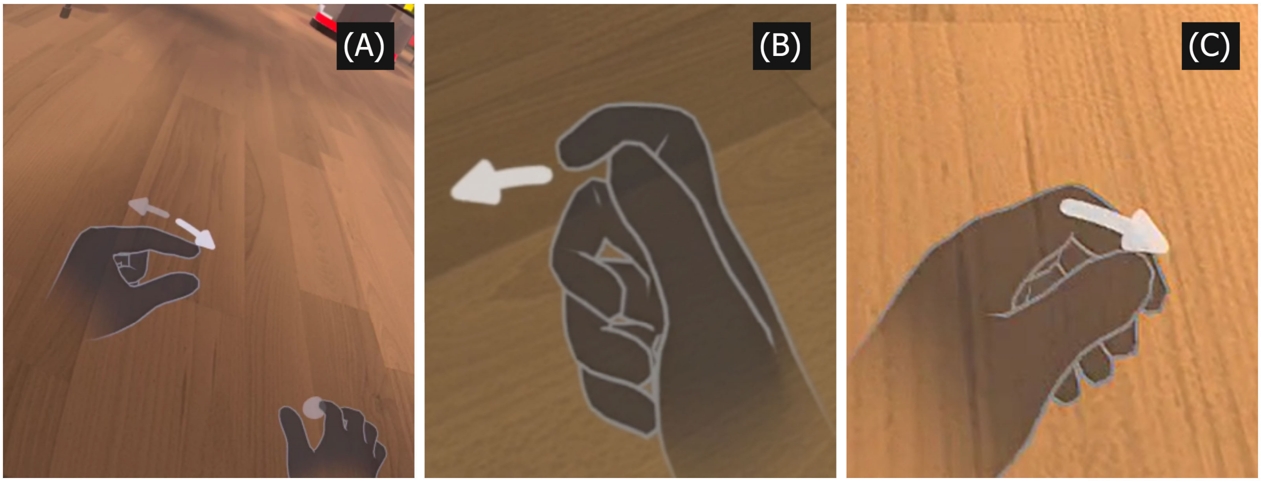

FIGURE 6. **Screenshots that shows the invocation of the arrows that allow virtual body rotation. (A) shows the base interaction, where a *pinch* over the arrow is required, (B) illustrates the adapted interaction with the left direction (right hand) and (C) shows the adapted interaction with right direction (left hand).**

Algorithm 4 Adaptation of the Invocation of Teleportation Arc and Turning Arrows

Data: boolean that checks if the handedness of the hand is right *rh*, a Vector3 that represents the up direction (0,1,0) in world coordinates *up*, a hand Pose object that contains the rotation and position of the hand obtained from hand-tracking data *HP*, the shoulder of the same body's half that the hand *sh*, boolean that controls if wrist rotation data is being collected *ic*, a public variable that stores the wrist rotation angle *angle*, an object that holds the script with the function HandleHandUpdated *wrist*, two floats that hold the minimum and maximum angles of wrist rotation *minAngle* and *maxAngle*.
Result: The rotation angle of the wrist adjusted to the handedness in every frame
function HandleHandUpdated
    Vector3 shoulderToHand ← (*HP*.position - *sh*.position).normalized
    Vector3 trackingRight ← Vector3.Cross(*up*, shoulderToHand).normalized
    trackingRight ← *rh* ? trackingRight: -trackingRight
    Vector3 wristDir ← *rh* ? -*HP*.forward: *HP*.forward
    wirstDir ← Vector3.ProjectOnPlane(wirstDir, houlderToHand).normalized
    wrist.angle ← Vector3.SignedAngle(wristDir, trackingRight, shoulderToHand)
    wrist.angle ← *rh* ? -angle: angle;
end function
while Update is called **do**
    if ic **then**
        float currentAngle ← *wrist.angle*
        currentAngle ← Mathf.Clamp(currentAngle, 0, 180)
        minAngle ← Mathf.Min(minAngle,currentAngle)
        maxAngle ← Mathf.Min(maxAngle,currentAngle)
        update the framecount to check if it has already passed 7 seconds
    end if
end while

which is further used in the Meta SDK. *ShoulderToHand* holds a vector with the direction of the shoulder to the hand, while *trackingRight* holds a vector that points to the right side relative to the direction of *shoudlerToHand*. *WristDir* holds the direction vector of the wrist, which is later reassigned to project the wrist direction onto a plane perpendicular to the direction pointed by *shoulderToHand*. An image that might help to understand the relationship between these vectors can be found in the following link https://github.com/AIR-Research-Group-UCLM/VR-Hands-Interactions-Adapted/blob/master/vectors.png. The function *HandleHandUpdated* is a callback function from one of the Meta SDK's library that we modified as shown in Algorithm 4. We would like to note that this pseudocode involves adjusting the sign of the variables, as well as the final angle, according to the hand where the script is attached.

IV. CASE STUDY: ADAPTED INTERACTIONS IN VR SHOPPING APPLICATIONS

To evaluate the suitability of the proposed adapted hand interactions for individuals with upper limb motor impairments, a case study was designed and executed, which will be presented in this section. For this purpose, a VR Shopping application prototype was developed using Unity 2022.3.15f1, as it allows us to evaluate the various proposed adaptations, as well as advance research on accessibility options in this type of virtual environment.

The two experimental sessions, conducted at the HNPT, involved a total of twelve participants (see Table 1), comprising ten patients and two healthy individuals (HNPT staff). All the patients had a chronic cervical SCI (more than one year after the injury). The sessions were conducted in two different days, spanning a duration of five hours each. The inclusion of two healthy participants was not meant for statistical comparison with the group of ten users with disabilities, but rather to ensure usability, validate feasibility, and obtain expert opinions on accessibility adaptations.

The primary objective of the experimental sessions was to conduct a functional analysis. This analysis enabled an early assessment of the tool's safety and efficacy, ensuring that potential risks were identified and mitigated before expanding the patient pool. It also provided an opportunity to identify and resolve any technical or operational challenges in a controlled setting, which is crucial for successful project scaling. Moreover, this approach facilitated the validation of research methodologies, including data analysis protocols, ensuring their robustness and reliability for a large-scale study.

In addition to the functional analysis, other objectives of the experimental session included assessing the well-being of users in the VR environment and gathering their personal feedback on its application in rehabilitation. This involved understanding their comfort levels and subjective opinions about the tool's role in their recovery process. In addition, our goal was to track any improvements in exercise performance during the course of the session, focusing on how quickly and effectively users could adapt to the exercises in the virtual setting.

A. RESEARCH QUESTIONS

The case study aims to answer the following research questions:

1) (RQ1) Do adapted interactions enable people with motor impairments to perform tasks in immersive spaces?
2) (RQ2) Do adapted interactions improve the performance of a person with motor impairment when performing tasks in immersive spaces?
3) (RQ3) Do users positively evaluate adapted interactions in terms of usability and user experience?

To address these questions, data was collected during the execution of two experimental sessions with 10 patients from HNPT, a biomechanical engineer and a therapist. These data were obtained from non-invasive sources for the participants and can be classified as: i) interaction data, ii) head and hand tracking data, and iii) positional and kinematic data. In addition, a questionnaire was prepared for the participants to evaluate their experience based on various standardised questionnaires. We compiled questions from NASA-TLX [16] to assess workload, the System Usability Scale (SUS) [6] to determine usability of adaptations, the User Experience Questionnaire (UEQ) [39] to collect feedback on user experience, and the Motion Sickness Assessment Questionnaire (MSAQ) [14] to measure the degree of motion sickness caused.

The next section describes the methodology of the study carried out.

B. DESCRIPTION OF THE VOLUNTEERS

For the execution of the case study, we collaborated with HNPT patients and staff. All participants gave us their consent to use the data obtained during the experimentation, as well as to participate in the case study. Table 2 shows the mean and standard deviation (SD) of various parameters to characterise the degree of neurological injury of the study participants. The use of average data to characterise patients is the standard in clinical studies. Patients had a SCI between the metameric levels C2 (cervical injury) and D8 (dorsal injury), and neurological classification according AIS (ASIA Impairment Scale) [24] between A (complete lesion in motor and sensitive aspects) and D (incomplete injury in the motor and sensitive aspects). The right arm was dominant in 90% of the patients, and was the treated arm in 70% of them. The UEMS (Upper Extremity Motor Score) for the treated arm was 14.14 (SD = 8.62), reflecting the impairment in upper extremity function, as assessed through the evaluation of five specific upper extremity muscles. The maximum score, 25 points, is reached for neurologically healthy subjects. By means of the SCIM scale (Spinal Cord Independence

TABLE 1. Volunteers' age and relationship with HNPT.

User	Age	Status within HNPT
U1	14	Patient
U2	28	Patient
U3	34	Patient
U4	21	Patient
U5	42	Patient
U6	48	Patient
U7	19	Patient
U8	54	Patient
U9	22	Patient
U10	48	Patient
U11	44	HNPT's Biomechanical Engineer
U12	38	HNPT's therapist

TABLE 2. Characterisation of the degree of neurological injury of the case study participants.

	SCI Patients (n=10)	Healthy subjects (n=2)
	Mean (SD)	Mean (SD)
Male	10.00 (100.00)	1.00 (50.00)
Age	32.00 (13.22)	41.00 (4.24)
Injury level	C2-D8	-
AIS scale	A-D	-
Dominant arm (Right)	8.00 (80.00)	2.00 (100.00)
Treated arm (Right)	7.00 (70.00)	2.00 (100.00)
UEMS treated arm	14.14 (8.62)	25.00 (0.00)
SCIM (0-100)	48.00 (25.25)	100.00 (0.00)

FIGURE 7. Photographs taken during experimental sessions at the National Hospital for Paraplegics with patients suffering from spinal cord injuries and having motor limitations in legs, arms, and hands.

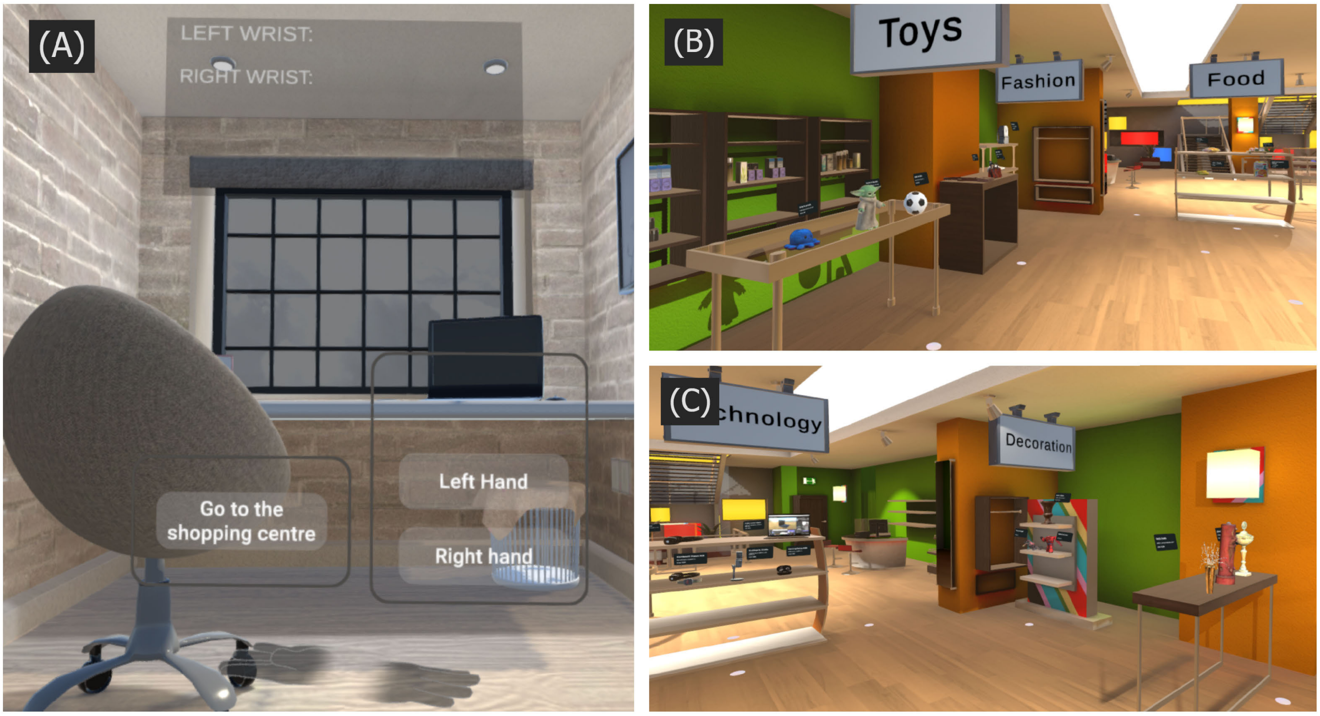

FIGURE 8. Two screenshots of the environments used in the case study. (A) shows the environment where wrist rotation angles were obtained, B and C shows two points of view of the environment used for the case study.

Measure) [7] was used to evaluate the independence level of the patients, scored between 0 and 100. In this scale a higher score corresponds to a higher degree of independence. In combination with this characterisation, the knowledge and experience of the HNPT staff was of great help in designing the tailored interactions, as it gave us a more complete picture of the patients' limitations. Thus, we always had in mind to develop the adaptations as generically as possible so that any patient could use them regardless of whether they had more or fewer limitations. In the case of the patients, we asked which of their upper limbs was most affected by their motor impairments (treated arm in Table 2). This information was crucial, as they were later asked to use their most affected limb during VR environment sessions with adapted interactions. In the case of participant U4, the patient expressed that both limbs were similarly impaired.

C. METHODOLOGY

To determine whether the adapted interaction mechanisms help individuals with motor issues complete the proposed tasks and whether there is an improvement in their performance, the following experimental session flow was designed:

1) Each volunteer was shown the environment in which he or she would be immersed during the session in a video, with a particular emphasis on the products and sections relevant to the tasks.
2) Next, the users were introduced to the different ways of interacting in the non-adapted environment, and they were given between 1 to 2 minutes of prior training in an environment different from the one used in the experiment. It was emphasized that the non-adapted interactions could be difficult to perform, and they were encouraged not to become overly frustrated.
3) After this, they began performing the tasks listed in Table 3. One of the authors guided them, indicating the objective of the next task after completing the previous one.
4) Once this first execution was completed, the adapted interactions and how to perform them were introduced. In this case, no prior training was provided, to later assess how simple and user-friendly the adapted interactions were, considering they were already familiar with the environment.
5) Before the execution of the adapted environment, Algorithm 4 was applied in an additional scene created with Unity (see Fig. 8.A) to utilize the wrist rotation angles obtained in the case study.
6) During the execution in the adapted environment, the same author guided the participants through the same tasks in the same order.
7) After both executions, the participants were asked to complete the questionnaire prepared for the study.

To avoid causing excessive fatigue for the volunteers, the following measures were taken. First, the total experimental time for each participant was limited, with an ideal duration between 25 and 30 minutes to explain, conduct the training in non-adapted interactions, experiment with both environments, and complete the questionnaire. Based on our previous experience and the knowledge of the hospital staff, experimental sessions of longer duration cause considerable mental and physical fatigue in patients, causing them to lose concentration and provoking a desire to finish as soon as possible. Second, in the event of a participant abandoning a task in the non-adapted environment, such as navigating through the environment, one of the authors would intervene to position them for the next task. In these cases, the task was marked as failed or incomplete. Volunteers were encouraged to prioritize their health and avoid overexertion or compensating with unaffected parts of their body.

After formulating the research questions and determining approximate time limits for the tasks based on previous data, the tasks described in Table 3 were proposed for the case study participants. The fourth link of this. txt file from tout Github repository shows one of the authors conducting each of the tasks described in the table: https://github.com/AIR-Research-Group-UCLM/VR-Hands-Interactions-Adapted/blob/master/video_link.txt. All tasks, except the last one, were guided, meaning that the section and product were predefined for the participant. This decision was made to allow for more precise and objective comparisons of results, given that the same situation would be presented to all volunteers across both environments, as will be discussed below. Even though it may seem that the number of tasks is not balanced according to the number of adapted interactions shown, note that grabbing tasks inherently require movement within the environment. Therefore, teleportation and virtual body rotation are implicit actions needed to complete such tasks.

We did not consider adding the removal of a product from the shopping cart since the user's position and movements are practically the same as when adding a product. Additionally, we must take into account the physical and mental load that long experimental sessions impose on patients with spinal cord injuries. The fatigue experienced when performing an activity is greater than that of a healthy person, especially in muscles such a the elbow flexors [40].

D. MATERIALS AND SOFTWARE USED

The materials used for the study were as follows:

1) MSI Raider GE68 HX 13V laptop with the following hardware: Intel i7-13700HX @ 2.1GHz, 32 GB RAM Memory, NVIDIA RTX 4060 8GB, Windows 11 64-bit.
2) Meta Quest 3 headset.
3) Optic fibre Link Cable for Meta Quest.

On the other hand, the software employed was as follows:

1) Unity 2022.3.15f1 for the design and development of the applications used in the experimental sessions.
2) Meta XR All-in-One SDK v59.0 to integrate the Unity application with the Meta headset.
3) Meta Quest Link application for PC to run the application during the experimental sessions.
4) Microsoft Forms for creating the questionnaire and collecting responses.

E. CASE STUDY LIMITATIONS

The sample of volunteers with motor difficulties may seem small. However, we must consider the challenges associated with recruiting individuals with these types of injuries for experimental sessions. In addition to travelling to HNPT, we must consider the patients' tight schedules at the hospital, as rehabilitation and physiotherapy activities often consume much of their time. Furthermore, we must account for the dependency of these individuals, which means that neither them nor their caregivers are always available. We also decided to include two biomechanical engineers in the sessions, who work regularly with these patients, to provide feedback on the adaptations. However, the results presented in Section V show a clear trend among patients with SCI, and thus we consider the sample sufficient to answer the research questions posed.

Another limitation to consider is that this case study does not conduct long-term follow-up. Nevertheless, in the context of this work, as shown in Section V, it can be seen that the adapted interactions helped the volunteers perform tasks they could not previously accomplish or improve their performance in executing them. This case is not the same as one that monitors the long-term influence on a patient's recovery or rehabilitation.

The VR application was developed using Unity and the Meta SDK for the Meta Quest headset line. This decision was driven by three main factors: (i) the authors' experience in developing VR applications with this SDK, (ii) Meta's leading position in the VR device market,[5] with a substantial advantage over competitors, enabling it to reach a larger potential user base, and (iii) the Meta SDK provides direct integration with hardware-specific features of the Meta Quest headsets that are particularly relevant for the case study. These features include advanced hand tracking, allowing precise and high-frequency tracking, as patients may suffer trembling during the usage of the application, causing undesired outcomes if the tracking is not precise enough. Additionally, the abstraction layers and the ability to modify the interaction mechanisms provided by the SDK led to the decision to use the Meta Quest 3 for the case study. While this may initially seem like a significant limitation, the Meta SDK is compatible with the OpenXR standard, facilitating the potential future porting of the application to this standard.

Lastly, one could consider a limitation the fact that the same virtual environment was used for both interactions. However, this allows us to objectively and directly compare the actions taken to complete a given task, whether it was completed or not, as well as the time spent on it.

V. RESULTS

In this section, we will present the results obtained from the analysis of the data extracted from the experimentation, as well as the responses to the questionnaire.

[5]https://techwireasia.com/2023/07/meta-headset-sales-outperform-other-brands-in-2023/

TABLE 3. Tasks to be performed by volunteers of the case study. In the case of Task #6, 4 more seconds are added to compensate the user movement of reaching an object that is placed high in the shelf.

Task ID	Description	Minimum number of interactions required	Consideration for the adapted interaction
#1	Move to the "Toys" section	It requires 1 teleportation	-
#2	Grab the Baby Yoda stuffed toy and release it	Grab + moving to the shopping cart	Release made by pointing to the bin (see Fig. 2.D)
#3	Turn your body using the arrows until you see the table where the Burner is	Volunteer can turn using either left or right hand directions. 3 turns are required	Volunteer can turn using either left or right hand directions (see Fig. 6.B and C)
#4	Move to the "Decoration" section where the Burner is	It can be performed within 1 teleportation	Volunteer might need to turn itself in the virtual environment
#5	Grab the Burner and add it to the shopping cart	It requires grab and addition to shopping cart shopping cart	Volunteer might add it through distance or manually (see Section III-A2)
#6	Move to the "Fashion" section	It requires 2 turns and 2 teleportation	-
#7	Grab the Backpack and add it to the shopping cart	Grab in a high shelf + move to the shopping cart	Volunteer might not be able to grab it in the non-adapted environment
#8	Move again to the "Toys" section	It requires 1 turn and 2 teleportations	Volunteer might need to turn itself in the virtual environment
#9	Grab the Ball and add it to the shopping cart	Grab with both hands is required.	-
#10	Add to the shopping cart the product of your desire	Depends on what each user wants to add	Free exploration task. Volunteer cannot add a product from "Toys" section

A. QUANTITATIVE ANALYSIS

The quantitative analysis regarding the degree of improvement provided by the adapted interactions focuses on a study of effectiveness and an estimation of effort during task completion in the immersive space. Both studies help provide answers to Research Questions $RQ1$ and $RQ2$ at the end of the section.

1) EFFECTIVENESS

Table 4 shows the time, in seconds, that each user took to complete each task in both environments, unadapted and adapted (tasks described in Table 3). Cells highlighted with a gray background indicate that the user abandoned the task without completing it. The time reflected in these cells corresponds to the duration the user spent trying to perform the necessary interactions before abandoning it due to fatigue or their inability to complete the task because of motor limitations. The last row indicates the percentage of tasks completed in each VR environment by each user. Among the volunteers, it is worth noting that U2, U5, U6, U7, U8, and U10 were the ones who were least able to complete tasks in the unadapted environment due to their injuries and limited mobility.

It is important to point out that, in the case of the first three tasks in the unadapted environment, we asked users to attempt the tasks using their most impaired hand so that they could later assess the impact of the adapted interactions. Notably, tasks #4, #6, #8, and #10 took the most time in both environments, as they involved the most movement around the environment, either via teleportation or virtual body rotation. However, it is evident that users with injuries to both hands had a high abandonment rate, reflected in the tasks within the unadapted environment. The tasks that took the least time for users were those related to object grabbing and adding items to the shopping cart. In terms of effectiveness, we observe that all users were able to complete all tasks in the adapted environment, demonstrating that these interactions significantly improved the effectiveness of users with injuries in interacting with the environment.

Fig. 9 shows, for each user, the percentage of performance gain when performing the same task in the environment with adapted interactions compared to the same task in the unadapted environment. We can observe a general trend of performance improvement when using adapted interactions. Specifically, tasks involving movement through the virtual environment show increases of up to 91.6%. Tasks with lower increases, or even in some cases negative increases, are those related to grasping, particularly two-handed grasping. This may be due to the waiting time established for performing auto-grasp when the virtual hand comes into contact with the object. It is also important to consider that, for instance, in tasks #5 and #7, if the user opts for distance grasping, they must also wait a certain amount of time while pointing at the object, plus the time it takes for the object to move towards the hand to perform the auto-grasp. Finally, it is noteworthy that healthy users, U11 and U12, show worse performance in some tasks with the adapted interactions. Despite this, one possible reason could be the need for them to simulate having no hand mobility, in addition to the required waiting times for grasping and teleportation.

Taking these waiting times into account, we can perform a paired t-test taking into account the data collected from U1 to U10 (HNPT's patients) with the following hypotheses:

1) H_0: There is no significant difference in task completion times between using unadapted and adapted interactions.
2) H_1: There is a significant difference in task completion times between using unadapted and adapted interactions.

Thus, we obtain that $t - statistic = 5.75$ and $p - value = 7.06 \times 10^{-8}$. The former indicates a significant difference in

TABLE 4. Time in seconds spent by each user on every task in both Unadapted (U) and Adapted (A) environments. Cells with grey background mean that the user could not complete the task by itself. The time showed is the time they spent trying to carry out the task before abandoning it. The thicker vertical line is used to separate injured users (U1-U10) between healthy users (U11 and U12). C.R. % stands for Completion rate.

User	U1		U2		U3		U4		U5		U6		U7		U8		U9		U10		U11		U12	
Task	U	A	U	A	U	A	U	A	U	A	U	A	U	A	U	A	U	A	U	A	U	A	U	A
#1	30.50	8.40	26.20	5.57	20.05	5.97	22.36	6.46	51.24	7.68	59.65	6.48	70.09	5.86	43.10	9.97	22.36	5.47	34.16	8.43	8.89	6.73	11.09	5.01
#2	13.50	6.50	8.99	7.46	13.46	7.97	12.07	7.01	9.40	9.12	10.75	7.82	12.90	9.97	10.13	6.90	12.97	7.39	12.33	7.26	4.29	7.37	6.39	8.15
#3	33.90	13.38	32.04	16.01	36.88	7.57	38.51	13.70	62.34	18.76	43.82	10.60	76.47	13.90	96.13	18.77	29.18	12.68	69.03	18.10	9.59	11.76	11.99	6.08
#4	22.93	10.97	30.39	6.19	43.16	8.33	16.36	12.69	73.04	22.48	22.64	15.05	28.37	16.39	74.80	13.03	23.47	8.68	64.53	19.42	5.17	5.71	7.24	6.43
#5	19.67	10.46	12.19	10.15	16.65	8.94	15.00	7.83	18.04	12.40	25.18	8.46	14.14	12.05	24.32	8.86	18.78	9.94	9.31	10.26	5.82	6.15	7.36	6.95
#6	36.96	13.51	42.89	10.87	36.03	23.81	27.37	18.90	46.19	21.30	58.87	22.80	26.44	16.29	105.51	22.01	22.18	20.50	71.67	28.47	10.33	10.04	14.42	12.03
#7	16.46	8.01	13.64	8.40	12.50	10.10	36.78	7.17	36.78	8.96	21.32	7.67	52.54	11.99	35.23	16.99	13.35	9.44	19.32	6.87	5.85	7.17	10.90	8.15
#8	24.87	18.61	43.37	21.40	45.08	30.35	30.00	16.47	55.52	27.37	46.93	20.54	25.37	18.10	46.23	33.32	43.22	20.73	26.56	23.36	10.72	15.43	17.65	18.43
#9	18.94	14.22	13.61	16.00	13.68	10.53	14.04	11.56	17.04	17.17	15.35	11.03	11.83	12.49	27.43	8.05	15.64	10.68	16.93	14.46	8.29	10.18	7.85	12.89
#10	34.14	28.56	48.88	18.96	28.00	20.89	36.94	23.29	49.04	35.58	75.45	30.43	49.79	42.40	64.38	37.19	44.99	28.40	57.93	44.47	20.00	14.90	21.01	24.50
C.R.	80%	100%	30%	100%	50%	100%	50%	100%	0%	100%	10%	100%	30%	100%	0%	100%	60%	100%	30%	100%	100%	100%	100%	100%

FIGURE 9. Bar graph per user showing the increased performance in the Adapted environment against the Unadapted environment.

terms of standard deviation between the times. Additionally, the latter is a value far below the common significance threshold of $\alpha = 0.05$. Given that the p-value is much smaller than the significance threshold $\alpha = 0.05$, we reject the null hypothesis H_0 and accept the alternative hypothesis H_1. This means that there is statistically significant evidence of a difference in task completion times when using adapted interactions compared to unadapted ones. The t-statistic also supports this conclusion, as such a high value indicates a significant difference between the means of the two groups.

2) EFFORT ESTIMATION

Having demonstrated that the adapted interactions helped users complete tasks that they could not perform before, and in less time, we will now estimate the effort they had to exert with both types of interaction. To do this, we will inspect the

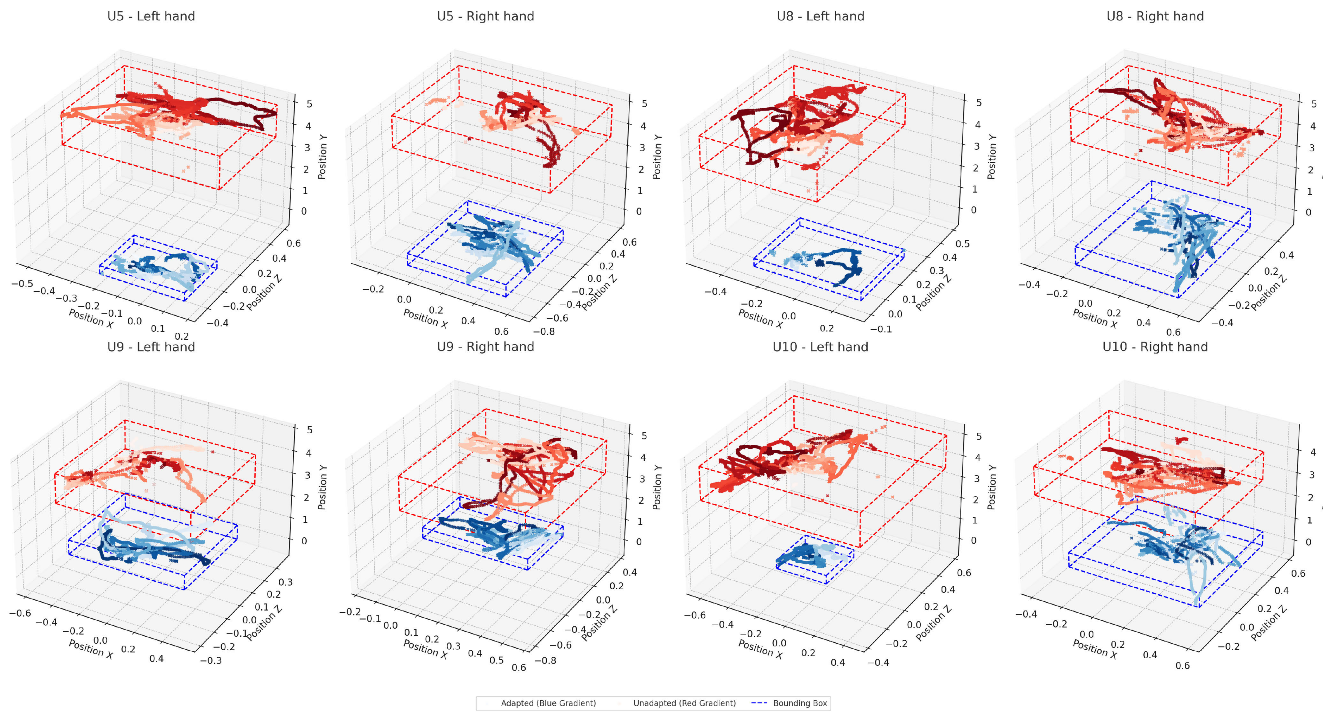

FIGURE 10. Hand movements made with the hands by some volunteers during the case study. These subgraphs include all the movements made for every task. These movements are translated in the Y axis to ease the readability of the movements and avoid superposition. The gradient in the colours indicates the passage of time: the colour starts very warm at the beginning of the user's session and progressively increases towards cooler colours. The bounding boxes encapsulate the range of movement of the hands by each of the users. The legend of the 3D charts indicate: Red colour - Unadapted, Blue colour - Adapted.

spatial movement data recorded during the experimentation phase.

Figure 10 shows the hand trajectories of some of the injured volunteers during the case study. A Z-score filtering has been used to remove outliers likely caused by tracking errors. As can be observed, each volunteer with injuries performs movements differently, depending on their motor capabilities and height. However, one general characteristic is visually apparent: the graphs representing the adapted interactions appear more compact, while those representing the unadapted interactions are broader and less condensed. This implies movements of greater amplitude and more erratic patterns, which could indicate higher effort and discomfort for users with spinal cord injuries. These movements may be due to the users attempting to perform the required interaction for a task by adjusting their limbs according to their degree of injury.

In an effort to quantify this apparent trend in the degree of effort exerted, we will attempt to estimate the difficulty faced by each user based on the spatial tracking data of the users' hands, the number of attempts made to complete each task, and the time taken to either complete or abandon each task, as previously presented in Section V-A1. Having described in Section II the works in literature to evaluate physical effort and the difficulty encountered in VR case studies, a significant reliance on qualitative data from questionnaires for such assessments was identified. However, the quantitative data used largely depended on the context of the task, such as the completion time. Moreover, other data to estimate physical effort is used for rehabilitation purposes and depends on other hardware tools such as haptic gloves to determine pinch strength precisely [33]. Therefore, based on these studies and the limited use of motion data obtained through VR headset hand tracking systems, we propose two quantitative metrics to estimate the difficulty encountered and the physical effort made by volunteers in our case study.

The Difficulty Index (DI) is a metric we developed, taking into account various characteristics extracted from the hand tracking data of volunteers during the case study. The index returns a value in the range [0,1], quantifying the difficulty encountered by the user based on their recorded movements. Below, we present the formula and a detailed description of its components.

Before describing the components of the index, we must first contextualize the data collection process and its implications. The application running on the Meta Quest 3 operated at an average frame rate of 72 frames per second (fps), recording spatial tracking data at each frame with four significant decimal digits of precision. This implies that the difference in the recorded coordinates between one row of the generated CSV files and the next is generally minimal, as 72 rows of data are stored per second. This provides detailed data records, but the noise generated by small, involuntary movements must be filtered out before meaningful information, such as actual movements or distance travelled, can be obtained. To achieve this, a Kalman filter [43] was applied to eliminate noise, making the changes in the data smoother and more representative of the actual movement performed.

The Kalman filter used is a simplified version that does not require complex state transition models, as the goal is simply to smooth the collected data. Thus, the filter consists of the following steps:

1) Prediction.

$$x_k = x_{k-1} \tag{1}$$

where x_k is the prediction of the state at time k (smoothed position), and x_{k-1} is the corrected state at the previous time step. Here, we assume that the previous state is the best prediction for the next.

2) Covariance of the state and its prediction. The covariance P_k predicts the uncertainty of the estimation.

$$P_k = P_{k-1} + Q \tag{2}$$

where Q is the process noise. Q is parametrizable, and in our context, $Q = 0.001$ since the uncertainty in the position change between two consecutive frames is minimal.

3) Correction with the measurement (Kalman Gain)

$$K_k = \frac{P_{k|k-1}}{P_{k|k-1} + R} \tag{3}$$

where R is the covariance of the measurement noise and $P_{k|k-1}$ is the covariance estimated in time k based on the information available until time $k-1$. K_k quantifies how much to trust the prediction compared to the new measurement. In our context, $R = 0.01$ represents a low value because our measurements contain insignificant noise, with only small changes due to the high measurement frequency (72 Hz). Therefore, the measured data is highly reliable.

4) Correction of the state with the measurement.

$$x_{k|k} = x_{k|k-1} + K_k \times (z_k - x_{k|k-1}) \tag{4}$$

where $x_{k|k-1}$ represents the prediction of the state at time k based on the available information at time $k-1$, before knowing the new measurement at time k. Thus, $x_{k|k}$ is the corrected or smoothed state estimate at time k, incorporating the new measurement z_k and the Kalman gain K_k.

5) Covariance correction.

$$P_{k|k} = (1 - K_k) \times P_{k|k-1} \tag{5}$$

where the uncertainty of the state is updated for the next iteration.

The result of applying the filter to the dataset returns the corrected hand positions, $x_{k|k}$, resulting in a smoothing of minor fluctuations, allowing significant movements to be detected as changes in position while ignoring small changes caused by the high sampling frequency.

Taking this smoothing of the data into account, *DI* is represented by the following equation:

$$DI = \frac{NV_{BX} + N_{TD}N_{ME} + N_{MPS}}{4} \tag{6}$$

where NV_{BX} represents the normalized volume of the *bounding box* that encapsulates the range of motion for each hand, N_{TD} is the Euclidean distance between two points (i,j) covered by the hands, normalized, N_{ME} quantifies how efficiently the user has moved over a given number of frames, and, finally, N_{MPS} represents the number of movements per second (MPS). We wanted to include range of motion as it is one of the features used in the literature study regarding AR and VR applications in hand rehabilitation [33]. The parameters chosen for DI —movement volume, total distance traveled, movement efficiency, and number of movements per second— were selected based on their direct relationship with motor effort and precision, which are critical factors in assessing the difficulty experienced by users with mobility impairments. These parameters have been widely used in prior research to evaluate interaction complexity in VR and AR environments, particularly in rehabilitation contexts [22], [23]. The inclusion of these specific metrics ensures that DI captures different aspects of task execution: movement volume reflects the extent of hand displacement, total distance accounts for the overall effort required, movement efficiency quantifies precision, and movements per second indicate the control and stability of interactions. The letter N at the beginning of each component indicates that the data is normalized, as they have different scales, in order to assign equal weight in the calculation of the index. Therefore, the normalization process followed for each metric was the max absolute scaling. That is, divide each metric item by the maximum absolute value obtained for such metric from all volunteer's data obtained. This ensures us that the data items are within range [0,1]. The following paragraphs detail each of these characteristics:

1) NV_{BX}. The total volume of the *bounding box* in cubic meters (m^3) is calculated as follows:

$$\begin{aligned} V_{BX} = {} & V((\max(R_X) - \min(R_X)) \times (\max(R_Y) \\ & - \min(R_Y)) \times (\max(R_Z) - \min(R_Z))) \\ & + V((\max(L_X) - \min(L_X)) \times (\max(L_Y) \\ & - \min(L_Y)) \times (\max(L_Z) - \min(L_Z))) \end{aligned} \tag{7}$$

That is, the volumes of the *bounding boxes* for the left hand L and right hand R are summed, obtained by calculating the maximum and minimum values along the three-dimensional axes.

2) N_{TD}. The distance is computed for each of the used hands L and R in meters (m). This distance is calculated as following:

$$TD_h = \sum_{i=1,j=1}^{i=F,j,F} \sqrt{(X_i - X_j)^2 + (Y_i - Y_j)^2 + (Z_i - Z_j)^2} \tag{8}$$

where h represents the hand and F the number of records in the data file once the Kalman filter is applied. In order to consolidate the calculated distance into a single value, the arithmetic mean is computed: $\frac{TD_L+TD_R}{2}$

3) N_{ME}.We start with the assumption that the most efficient movement between two points in three-dimensional space is the straight-line distance that connects them:

$$D = \sqrt{(X_N - X_1)^2 + (Y_N - Y_1)^2 + (Z_N - Z_1)^2} \quad (9)$$

where N represents the last frame of the analysed sequence. On the other hand, the total distance covered between these points is:

$$D_T = \sum_{i=1}^{N-1} \sqrt{(X_{i+1} - X_i)^2 + (Y_{i+1} - Y_i)^2 + (Z_{i+1} - Z_i)^2} \quad (10)$$

A larger total distance covered may indicate more erratic and imprecise movements, which can be further compounded by the angle between consecutive frames to measure trajectory change by summing all the angles, such that:

$$\theta_T = \sum_{i=1}^{N-1} \theta_i = \sum_{i=1}^{N-1} arccos(\frac{(v_i \times v_{i+1})}{|v_i| \times |v_{i+1|}}) \quad (11)$$

v_i represents the displacement vector between points i and $i+1$. Lastly, redundant movements, where the user returns to a previous or very close position, are counted, indicating imprecision and a failure to stabilize the hand, for example, when trying to teleport. This allows us to observe hand stabilization and compare how the non-adapted interaction requires maintaining the hand shape while performing a *pinch*, whereas the adapted interaction does not require maintaining or forming a specific hand shape. To compute redundant movements, a threshold $\epsilon = 0.01$ centimeters is applied concerning the distance between consecutive points:

$$RM = \sum_{i=1}^{N-1} 1(distance(i, i+1) < \epsilon) \quad (12)$$

where $1(distance(i, i+1) < \epsilon)$ is a function that adds 1 if the distance is higher than the threshold ϵ. Thus:

$$ME = \frac{1}{\frac{D}{D_T} \times \frac{1}{1+\theta_T+RM}} \quad (13)$$

This final inversion is done so that low efficiency values have a greater impact on increasing the value of the DI, giving us a dimensionless score. Taking into account both hands, the final value is $\frac{ME_L+ME_R}{2}$

4) N_{MPS}. Number of movements per second (MPS), normalized. A higher number of movements per unit of time contributes to user fatigue, indicating that they are facing greater difficulty and require more movements to try to accomplish the task. Thanks to the Kalman filter, we can compute each movement as the distance between two consecutive points i and $i+1$, establishing a threshold $\epsilon = 0.01$, which, as before, refers to 1 cm. Taking into account both hands, the final value is $\frac{MPS_L+MPS_R}{2}$.

Our decision to normalize over the population was driven by the need to ensure fair comparisons among users with different levels of mobility. This was also suggested by expert staff of the hospital we collaborated with. Since the parameters used to calculate DI—such as movement volume, total distance traveled, movement efficiency, and movements per second—vary significantly between individuals, raw values would be inherently biased by each user's motor capabilities rather than reflecting the relative challenge of the interaction. Normalization mitigates this issue by adjusting values within a common scale, allowing DI to capture differences in difficulty across participants rather than being skewed by individual limitations. Table 5 shows the values obtained for each component of the DI based on the collected data, as well as the DI value itself. It can be observed that, generally, the volume of the bounding box encapsulating the hand movements is smaller when using adapted interactions, which is consistent with what is shown in Fig. 10. A smaller movement range results in a smaller volume, indicating that the user was able to perform the movements more comfortably and in a more controlled manner, without having to compensate with other parts of the body, which would have resulted in a larger range of motion. Moreover, in general, the DI components related to movement show lower values in the adapted environments. This reduced number of movements, executed more efficiently and covering less distance, helps reduce user fatigue and indicates that the movements were performed more precisely and with greater control for the same purposes as with the unadapted interactions. We now calculate the percentage difference of the DI for each user as

$$PD = \frac{DI_A - DI_U}{DI_U} \times 100 \quad (14)$$

where DI_A is the score obtained for DI in the adapted environment and DI_U is the score obtained for DI in the unadapted environment. Therefore, we find that the overall mean is −37.06%, the median is −40.10%, and the standard deviation is 14.67%. In other words, users experienced an average reduction of nearly 40% in the required hand movements, as well as a smaller movement range and greater precision, resulting in less fatigue and perceived difficulty in completing the proposed tasks using the adapted interactions.

On the other hand, Table 6 shows the number of gestures or attempts made by a user in each task. Each attempt refers to the intention or success in making a hand shape or gesture required to perform an interaction. The effective execution of the interaction—for example, making the L-shape or attempting it with the hand—ecounts as 1 attempt, as does the pinch gesture or palmar grasp. In this case, the CSV

TABLE 5. Values of the components that make up the Difficulty Index (DI) and the final value of the DI for each user and each type of interaction used. In bold, adapted interactions' values are highlighted.

User	Interaction type	Bounding box volume	Total distance	Movement Efficiency	Movements per second	Normalized Volume (NV_BX)	Normalized Total distance (N_TD)	Normalized Movement Efficiency (N_ME)	Normalized Movements per second (N_MPS)	Difficulty Index (DI)
1	Unadapted	2.59	141.07	122882.88	6.29	1.0	0.56	0.2	0.67	0.49
1	**Adapted**	**1.16**	**71.38**	**105583.26**	**4.23**	**0.45**	**0.29**	**0.17**	**0.45**	**0.27**
2	Unadapted	1.54	114.05	190554.25	4.2	0.59	0.46	0.31	0.45	0.36
2	**Adapted**	**0.9**	**80.52**	**63884.47**	**7.4**	**0.35**	**0.32**	**0.1**	**0.79**	**0.31**
3	Unadapted	2.11	141.26	128044.12	9.35	0.81	**0.56**	0.21	1.0	0.52
3	**Adapted**	**1.97**	**80.4**	**135048.0**	**4.19**	**0.76**	**0.32**	**0.22**	**0.45**	**0.35**
4	Unadapted	1.74	90.13	160468.54	4.76	0.67	0.36	0.26	0.51	0.36
4	**Adapted**	**0.88**	**35.58**	**21700.54**	**2.03**	**0.34**	**0.14**	**0.04**	**0.22**	**0.15**
5	Unadapted	2.08	158.63	236371.68	4.51	0.8	0.63	0.39	0.48	0.46
5	**Adapted**	**0.84**	**89.65**	**110759.79**	**4.76**	**0.32**	**0.36**	**0.18**	**0.51**	**0.27**
6	Unadapted	1.62	221.77	359340.09	6.48	0.63	0.89	0.59	0.69	0.56
6	**Adapted**	**1.08**	**112.46**	**118344.92**	**7.59**	**0.42**	**0.45**	**0.19**	**0.81**	**0.37**
7	Unadapted	1.85	250.06	361796.36	7.21	0.71	1.0	0.59	0.77	0.61
7	**Adapted**	**1.18**	**91.11**	**67787.3**	**5.67**	**0.46**	**0.36**	**0.11**	**0.61**	**0.31**
8	Unadapted	1.55	170.54	609840.37	3.67	0.6	0.68	1.0	0.39	0.53
8	**Adapted**	**1.16**	**59.77**	**42681.67**	**1.96**	**0.45**	**0.24**	**0.07**	**0.21**	**0.19**
9	Unadapted	1.53	121.69	129441.35	6.56	0.59	0.49	0.21	0.7	0.4
9	**Adapted**	**0.77**	**67.15**	**60204.39**	**4.92**	**0.3**	**0.27**	**0.1**	**0.53**	**0.24**
10	Unadapted	2.45	215.86	583853.42	5.94	0.95	0.86	0.96	0.64	0.68
10	**Adapted**	**1.15**	**64.21**	**79041.2**	**2.67**	**0.44**	**0.26**	**0.13**	**0.29**	**0.22**
11	Unadapted	1.55	49.14	29673.7	8.97	0.6	0.2	0.05	0.96	0.36
11	**Adapted**	**0.84**	**71.31**	**41180.57**	**7.86**	**0.32**	**0.29**	**0.07**	**0.84**	**0.3**
12	Unadapted	1.23	73.04	65908.17	7.5	0.47	0.29	0.11	0.8	0.33
12	**Adapted**	**0.84**	**45.92**	**19028.54**	**6.05**	**0.32**	**0.18**	**0.03**	**0.65**	**0.24**

TABLE 6. Comparison of user interactions in adapted and unadapted environments. The table presents the number of attempts made by each participant for various tasks. The values represent the number of gestures or interaction attempts recorded during the study.

User	Environment	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
1	**Adapted**	**1**	**1**	**4**	**2**	**1**	**5**	**1**	**4**	**2**	**7**
1	Unadapted	17	1	4	8	3	12	2	9	3	9
2	**Adapted**	**2**	**1**	**8**	**2**	**3**	**5**	**1**	**6**	**2**	**4**
2	Unadapted	4	2	4	10	1	13	2	11	2	12
3	**Adapted**	**1**	**1**	**3**	**1**	**1**	**6**	**1**	**6**	**2**	**7**
3	Unadapted	8	1	4	15	1	17	1	10	4	11
4	**Adapted**	**2**	**1**	**6**	**1**	**1**	**4**	**2**	**5**	**3**	**5**
4	Unadapted	26	1	4	3	1	10	3	15	4	10
5	**Adapted**	**3**	**2**	**6**	**3**	**1**	**3**	**1**	**4**	**2**	**5**
5	Unadapted	19	2	9	17	2	-	3	-	4	2
6	**Adapted**	**2**	**1**	**3**	**1**	**3**	**6**	**1**	**4**	**2**	**7**
6	Unadapted	10	1	5	5	3	17	2	9	4	10
7	**Adapted**	**1**	**1**	**4**	**1**	**1**	**3**	**2**	**6**	**2**	**7**
7	Unadapted	9	1	5	6	7	-	4	-	5	5
8	**Adapted**	**2**	**1**	**5**	**3**	**1**	**8**	**3**	**6**	**1**	**9**
8	Unadapted	7	1	-	18	3	14	5	-	2	3
9	**Adapted**	**1**	**1**	**4**	**3**	**1**	**4**	**1**	**5**	**2**	**7**
9	Unadapted	9	1	4	8	1	9	2	9	4	9
10	**Adapted**	**1**	**1**	**5**	**1**	**3**	**6**	**1**	**4**	**2**	**10**
10	Unadapted	14	1	6	16	2	13	3	4	4	7
11	**Adapted**	**3**	**2**	**7**	**1**	**1**	**3**	**1**	**4**	**2**	**4**
11	Unadapted	3	1	3	4	1	7	3	8	2	10
12	**Adapted**	**2**	**1**	**6**	**2**	**1**	**6**	**1**	**7**	**2**	**7**
12	Unadapted	6	1	4	5	1	7	3	10	2	9

files recorded from each user allows us to determine when an interaction occurred, looking at he states of the relevant interactors for each interaction. In the case of adapted interactions, we recall that these gestures or hand shapes are simplified, counting as 1 attempt the fact of making such gesture. With both unadapted and adapted interactions, users could make attempts without carrying out the intended interaction. Delving into the Meta SDK code, certain classes allowed us to compute attempts. For instance, if a given threshold determine whether or not a pinch occurs, values lower than such threshold in a determined range help us determine that an attempt was made. Th API references for such classes we used are the following:

1) *FingerPinchGrabAPI* (https://developers.meta.com/horizon/reference/interaction /v71/class_oculus_interaction_grab_a_p_i_finger_pinch_grab_a_p_i). Helped us determine pinch/grab attempts as well as unadapted teleportations and turnings.
2) *FingerFeatureStateProvider* (https://developers.meta.com/horizon/reference/interaction/v71/class_oculus_interaction_pose_detection_finger_feature_state_provider). Helped us determine attempts related with gestures that trigger interactions (invoking teleportation arc, the arrows for turning or distance grab). This class uses recorded data from the Hand with the *Hand* class as well has thresholds for determining the state of fingers, *FingerStateThresholds*.

For volunteers U5, U8, and U7 in the unadapted environment, there are certain tasks in which no attempts were recorded. This is because the attempts made by the user did not exceed the required thresholds for the headset to detect the spatial position or required hand shape, meaning that the confidence levels provided by the Meta API were too low to detect these attempts. Additionally, this is combined with the fact that they abandoned the task before completing it, resulting in even fewer attempts.

Before addressing the research questions, we will consolidate into a single value: i) the time each user spent on each task ($Time_{Ti}$) and whether they completed it or not, ii) the number of attempts made ($Attempts_T$), and iii) the difficulty experienced by user U in the environment env, $DI_{U,env}$. Moreover, $Attempts_{max}$ and $Time_{max}$ represent the maximum values obtained for attempts and time in a single task T, respectively, over the user population, in order to normalize both terms. We will call this value the Effort Degree (ED), which is calculated for each task T and user U using the type

TABLE 7. Effort degree values taking into account number of attempts, time spent and difficulty index.

Task	U1		U2		U3		U4		U5		U6		U7		U8		U9		U10		U11		U12	
	A	U	A	U	A	U	A	U	A	U	A	U	A	U	A	U	A	U	A	U	A	U	A	U
#1	**0.55**	3.72	**0.67**	2.15	**0.52**	1.24	**0.7**	2.15	**0.91**	3.48	**0.68**	3.15	**0.37**	4.09	**0.58**	2.22	**0.42**	2.1	**0.35**	3.27	**1.12**	1.01	**0.61**	1.5
#2	**0.47**	0.63	**0.62**	0.46	**0.62**	0.48	**0.54**	0.48	**0.75**	1.34	**0.55**	1.31	**0.5**	0.45	**0.35**	1.23	**0.5**	0.56	**0.32**	0.39	**0.99**	0.43	**0.59**	0.54
#3	**1.32**	2.72	**2.29**	2.31	**1.03**	2.42	**1.83**	2.57	**1.94**	2.94	**1.06**	2.36	**1.18**	3.5	**1.26**	2.39	**1.26**	2.53	**1.11**	3.25	**2.29**	1.06	**1.37**	1.29
#4	**0.85**	1.63	**0.71**	1.89	**0.63**	3.48	**0.82**	0.73	**1.44**	3.77	**0.87**	1.93	**0.69**	2.67	**0.81**	3.61	**0.91**	1.97	**0.65**	4.19	**0.67**	0.9	**0.68**	1.12
#5	**0.65**	1.06	**1.11**	1.44	**0.66**	0.58	**0.58**	0.58	**0.65**	1.51	**0.97**	1.8	**0.56**	1.55	**0.42**	1.61	**0.61**	0.74	**0.65**	0.43	**0.7**	0.53	**0.53**	0.6
#6	**1.51**	2.54	**1.48**	3.55	**2.5**	3.43	**1.7**	2.49	**1.4**	1.92	**2.2**	3.78	**1.06**	1.56	**1.76**	3.72	**1.6**	3.09	**1.51**	4.04	**1.4**	1.65	**1.67**	1.84
#7	**0.54**	0.84	**0.68**	0.59	**0.72**	0.45	**0.74**	1.46	**0.53**	1.97	**0.54**	1.62	**0.74**	2.82	**0.94**	1.94	**0.59**	0.73	**0.31**	0.77	**0.79**	0.81	**0.59**	1.09
#8	**1.55**	1.79	**2.29**	3.36	**2.82**	3.14	**1.77**	2.84	**1.82**	2.11	**1.71**	2.8	**1.68**	1.53	**1.86**	1.67	**1.79**	3.74	**1.13**	2.04	**2.04**	1.82	**2.17**	2.45
#9	**1.0**	1.03	**1.31**	1.59	**0.96**	0.73	**1.34**	0.65	**1.04**	1.65	**0.89**	0.68	**0.76**	1.14	**0.39**	1.57	**0.82**	1.11	**0.64**	1.82	**1.23**	0.84	**1.01**	0.76
#10	**2.54**	2.17	**1.82**	3.62	**2.57**	2.71	**2.11**	2.83	**2.33**	2.13	**2.74**	3.48	**2.62**	2.94	**2.38**	2.19	**2.48**	3.8	**2.44**	3.09	**2.0**	2.72	**2.48**	2.53

of interactions i:

$$ED = \left(\frac{Attempts_T}{Attempts_{max}} \times \frac{Time_{Ti}}{Time_{max}}\right) \times (1 + DI_{U,env}) + 1(NotCompleted(T, U, i)) \qquad (15)$$

As can be seen, the terms for attempts and time are normalized so that neither predominates. On the other hand, the term $1 + DI_{Ui}$ ensures that there is always an impact of time and attempts on the effort, even if the DI is very low. Moreover, it ensures that the ED is amplified based on the DI obtained from the movements made by the user with their upper limbs. Finally, $1(NotCompleted(T, U, i))$ represents a function that adds 1 if the task T was not completed by U using the interactions i. Table 7 shows the results obtained, with the columns related to the adapted interactions highlighted in bold.

Observing Table 7, we can see the significant difference in effort considering the previously mentioned components. Those tasks where the values are not as significant, or where the resulting value is even lower in the unadapted interactions, are those exclusively related to object grasping: #2, #5, and #9. This may be due to the waiting times required for auto-grasp and distant grasping, as well as the injuries of each user, as those with both hands affected show an opposite trend to those who are healthy or have only one hand injured. This can also be seen in task #10, where, being the last task, users with more severe injuries abandoned the task earlier, resulting in fewer attempts compared to the same task with the adapted interactions. This also impacts time and DI, as the autonomy and ease provided by the adapted interactions allowed them to complete the task, making more movements and spending more time.

3) ANSWERING RESEARCH QUESTIONS

Having conducted the previous quantitative analysis, we will now address the following research questions.

a: RQ1: DO ADAPTED INTERACTIONS ENABLE PEOPLE WITH MOTOR IMPAIRMENTS TO PERFORM TASKS IN IMMERSIVE SPACES?

As demonstrated in Section V-A1, the adapted interactions allowed the injured users to complete 100% of the tasks in the shopping environment, enabling them to complete tasks they had to abandon when using unadapted interactions. This effect is particularly noticeable in patients with both hands injured, where the task completion rate is, at most, 30% of the proposed tasks. These interactions not only allowed them to complete the tasks without abandoning them due to fatigue but also significantly improved the time taken to complete them, as shown by the paired t-test conducted.

b: RQ2: DO ADAPTED INTERACTIONS IMPROVE THE PERFORMANCE OF A PERSON WITH MOTOR IMPAIRMENT WHEN PERFORMING TASKS IN IMMERSIVE SPACES?

As previously highlighted, Section V-A1 demonstrated the performance improvement achieved with the adapted interactions. However, this has been proven not only in terms of time and task completion but also in terms of the effort exerted and the difficulty encountered, as shown in Section V-A2. The reduced effort was due to a decrease in difficulty, facilitated by adapting the interactions to the users' upper limb impairments. This was demonstrated throughout Section V-A1. Additionally, we can perform a paired t-test concerning the ED:

1) H_0: There is no significant difference in the effort required to complete the tasks in the case study using the adapted interactions.
2) H_1: There is a significant difference in the effort required to complete the tasks in the case study using the adapted interactions.

We will compare all the values obtained for each task with the adapted interactions and those obtained with the unadapted interactions, shown in Table 7. Thus, we obtain $t-statistic = -6.79$, indicating that the mean values with the adapted interactions are lower. Furthermore, $p-value = 8.71 \times 10^{-11}$, which is much smaller than $\alpha = 0.05$, so we can affirm that there is a highly statistically significant difference in the effort required to complete the case study tasks using the adapted interactions, implying a lower effort.

To evaluate the relationship between the perceived difficulty reported by users and their performance in task completion, a Spearman correlation analysis was conducted between the DI and two key performance metrics: the task Completion Rate (CR) and the task Completion Time (CT), see Table 4. This analysis was performed separately for both the unadapted and adapted environments, allowing for a comparison of how these relationships vary depending on the presence of interaction adaptations.

The Spearman correlation coefficient (ρ) was chosen due to its suitability for non-parametric data, as it does not assume

TABLE 8. Questionnaire's questions along with the mean and standard deviation of answers per questions.

Question ID	Question	Scoring system	Mean		Standard deviation	
			A	U	A	U
Q1	How much experience do you think you have with the use of Virtual Reality (VR) glasses?	1 - None, 6 - A lot	**2.42**	2.42	**1.38**	1.38
Q2	Were the tasks very mentally demanding?	1 - None demanding, 6 - Really demanding	**1.50**	1.50	**0.80**	0.80
Q3	Were the tasks very physically demanding?	1 - None demanding, 6 - Really demanding	**1.91**	4.33	**0.79**	1.15
Q4	Did you have to make a great effort to carry out the tasks?	1 - None, 6 - A lot of effort	**1.75**	4.33	**0.97**	1.70
Q5	How frustrated, stressed or irritated did you feel?	1 - None, 6 - A lot	**1.50**	3.50	**0.67**	1.40
Q6	Did the interactions seem easy to use?	1 - Really easy, 6 - Really difficult	**1.67**	4.16	**0.89**	1.40
Q7	The interactions demotivated me from using the application	1 - Not at all, 6 - A lot	**1.33**	2.66	**0.65**	0.77
Q8	The interactions are understandable and easy to learn to use	1 - Strongly understandable and easy to learn, 6 - Very little	**1.58**	4.33	**0.51**	1.57
Q9	The interactions seemed friendly and appropriate for my limitations	1 - Very friendly and appropriate, 6 - Very little	**1.92**	4.50	**0.67**	1.56
Q10	I found it difficult to grab, release, move around the environment, and add products	1 - Very little, 6 - Very difficult	**1.50**	4.41	**0.67**	1.57
Q11	I would like to use these interactions frequently if I had to use the application	1 - Strongly agree, 6 - Strongly disagree	**1.67**	4.75	**0.65**	1.42
Q12	I think I would need help from a person with technical knowledge to use the system	1 - Strongly disagree, 6 - Strongly agree	**2.08**	3.50	**0.67**	0.90
Q13	I found the system very cumbersome to use	1 - Strongly disagree, 3- Neither agree nor disagree, 6 - Strongly agree	**1.50**	4.42	**0.90**	1.56
Q14	I felt very safe using the system	1 - Strongly agree, 6 - Strongly disagree	**1.33**	3.67	**0.49**	1.15
Q15	I felt very immersed in the virtual environment	1 - Strongly agree, 6 - Strongly disagree	**1.50**	1.50	**0.67**	0.67
Q16	I felt general discomfort or dizziness	1 - Strongly disagree, 6 - Strongly agree	**1.00**	1.00	**0.00**	0.00
Q17	I ended up with a headache	1 - Strongly disagree, 6 - Strongly agree	**1.17**	1.17	**0.39**	0.39
Q18	I felt blurred vision or eye fatigue	1 - Strongly disagree, 6 - Strongly agree	**1.25**	1.25	**0.45**	0.45
Q19	I felt tired	1 - Strongly disagree, 6 - Strongly agree	**1.17**	3.67	**0.39**	1.44

a normal distribution and effectively measures the strength and direction of monotonic relationships. The correlation was calculated as follows:

In the adapted environment, all users achieved a 100% completion rate, while in the unadapted environment, the completion rates varied depending on the users' motor abilities. For the CT, the total time taken to complete all tasks was calculated for each user in both environments. This allowed for an assessment of whether the DI was related to the time required to complete the tasks.

In the unadapted environment, the analysis revealed a moderate negative correlation between the DI and the task completion rate ($\rho = -0.578$, $p = 0.049$), indicating that users with higher DI scores completed fewer tasks. This suggests that the perceived difficulty had a direct impact on users' ability to complete tasks when no adaptations were in place. Additionally, there was a strong positive correlation between the DI and the task completion time ($\rho = 0.711$, $p = 0.009$), implying that users with higher DI scores required more time to complete the tasks. These results confirm that the DI reflects the real-world challenges faced by users, as greater perceived difficulty was associated with both lower success rates and longer completion times in the unadapted environment.

In contrast, in the adapted environment, the correlation between the DI and the task completion rate could not be computed because all users achieved a 100% completion rate. This lack of variability in performance outcomes indicates the positive impact of the adaptations, as they enabled all users to successfully complete the tasks regardless of their perceived difficulty levels. Furthermore, the correlation between the DI and the task completion time was not statistically significant ($\rho = -0.084$, $p = 0.794$), suggesting that users completed tasks in similar amounts of time regardless of their DI scores.

These findings highlight a clear distinction between the two environments. In the unadapted environment, the DI is strongly correlated with performance metrics, confirming that it accurately reflects the difficulties encountered by users

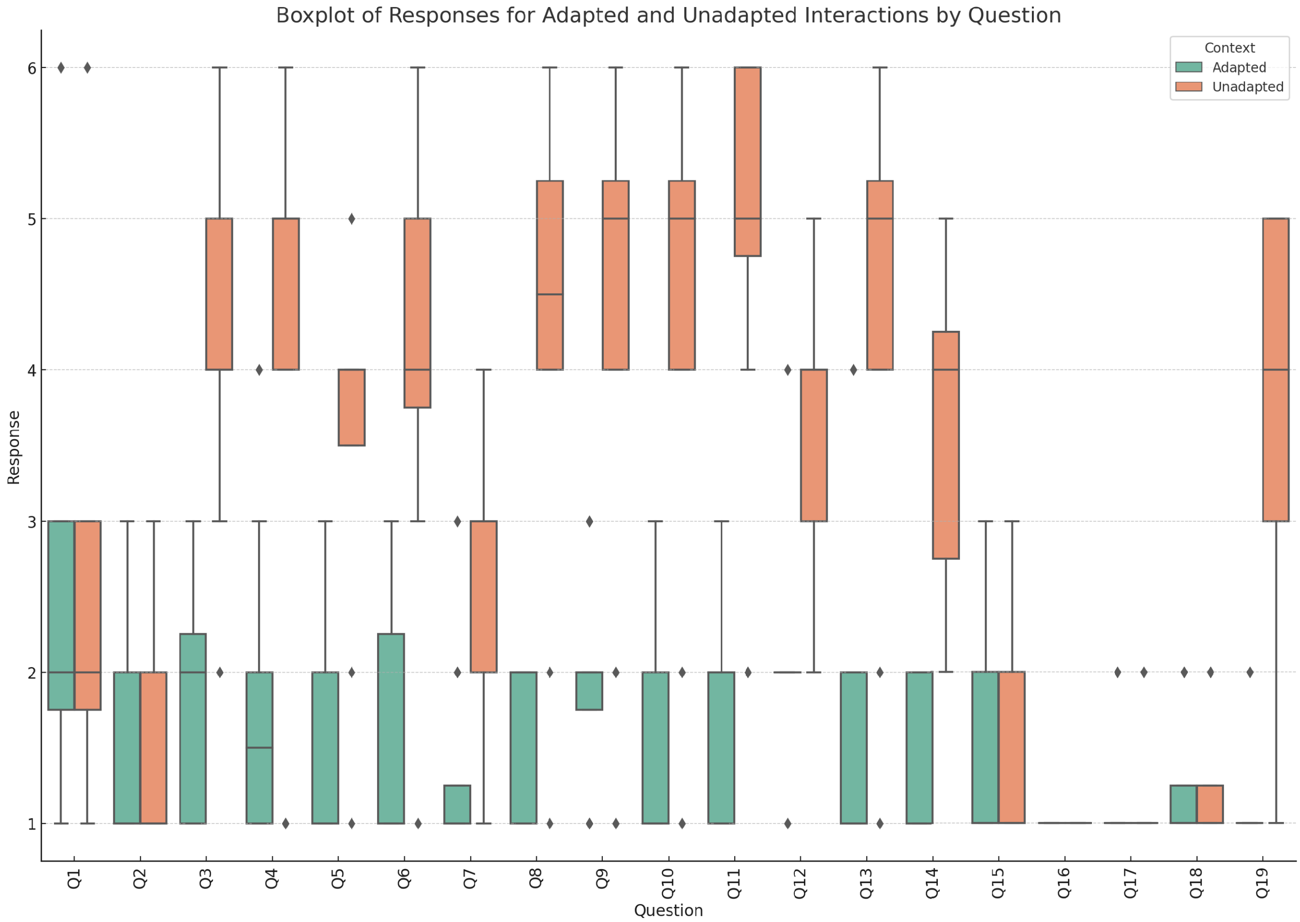

FIGURE 11. **Boxplot of the questionnaire responses, containing two boxes per question.**

without interaction adaptations. On the other hand, in the adapted environment, the absence of significant correlations indicates that the adaptations effectively mitiagated the impact of perceived difficulty on task performance. Even users who reported higher levels of perceived difficulty were able to complete tasks successfully and in comparable times to those with lower DI scores.

Importantly, the lack of correlation in the adapted environment should not be interpreted as a limitation of the DI. Rather, it serves as evidence of the success of the implemented adaptations. By reducing the influence of users' motor limitations, the adaptations created a more inclusive environment where performance disparities based on individual capabilities were minimized. This outcome is analogous to universal design principles, where accessibility improvements, such as ramps or assistive technologies, eliminate barriers without creating performance gaps between different user groups.

B. QUALITATIVE ANALYSIS

Next, we will analyse the responses to the questionnaire that each user completed after using both the adapted and the unadapted interactions. The volunteers answered the same questions considering their experience and feelings with both types of interactions. In cases where the questions were not intrinsically related to the types of interaction, the responses were identical.

Table 8 presents the questions from the questionnaire, as well as the mean and standard deviation of the 12 responses to each question within the two contexts: with the adapted interactions highlighted in bold and the unadapted interactions not highlighted. Additionally, to statistically analyse these responses, Fig. 11 shows a boxplot containing two boxes for each question. These plots summarize the distribution of a dataset and visualize its key features, with the box representing the interquartile range containing 50% of the data, the central line corresponding to the median, and the whiskers extending from the box with outliers shown outside them. The orange boxes represent the responses regarding the unadapted interactions, while the green boxes represent those for the adapted interactions. On one hand, we can clearly observe an opposite trend between both contexts. Additionally, the outliers in the responses to the unadapted interactions correspond to healthy HNPT staff, who perceived

TABLE 9. Wilcoxon Signed-rank test p-values obtained from the questionnaire's responses.

Question ID	Wilcoxon p-value
Q3	0.0005
Q4	0.0045
Q5	0.0066
Q6	0.0048
Q7	0.0050
Q8	0.0046
Q9	0.0041
Q10	0.0045
Q11	0.0046
Q12	**0.0069**
Q13	**0.0069**
Q14	0.0041
Q19	0.0046

these interactions as more typical from their perspective. In the case of the unadapted interactions, we also observe elevated medians in questions such as Q9, Q10, Q11, and Q13.

We will analyse these results by grouping the questionnaire questions into categories:

1) **Physical and mental demand**. In Q2 (mental demand), the responses are consistent in both contexts, with a low median and minimal dispersion. This suggests that users perceived a low mental load in both the adapted and unadapted contexts. However, in Q3 (physical demand), the differences are much more pronounced. The unadapted interactions show a higher median, with considerably greater dispersion compared to the adapted ones. This indicates that, while some users did not perceive a significant increase in physical demand, others experienced much higher levels of physical effort in the unadapted context. Q4 reinforces this trend, showing greater variability and a considerably higher median. This confirms that physical effort was perceived as more demanding in the unadapted context, whereas in the adapted context, the responses are more clustered toward the lower end of the scale.
2) **Usability and comprehension**. The responses related to ease of use (Q6, Q13) show a clear difference between contexts. With the adapted interactions, responses are concentrated at lower values, with limited dispersion, indicating that most users found the interactions easy to use. In contrast, the unadapted interactions show greater dispersion and a significantly higher median, suggesting more variability in user experience and a general perception of greater difficulty. Similarly, Q8 (understandability of the interactions) and Q9 (friendly and appropriate interactions) present a pattern where the adapted interactions are perceived as more accessible and easier to understand, while the unadapted interactions are seen as more complex, with greater variability in the responses. Finally, Q12 shows very concentrated responses with the adapted interactions, unlike the unadapted ones, where there is a greater perceived need for technical assistance.
3) **Frustration and motivation**. Questions Q5 (frustration) and Q7 (demotivation) reveal a similar pattern. In both cases, the median and dispersion with the unadapted interactions are notably higher, indicating that, for many users, the unadapted context generated more frustration and demotivated them from using the application. In contrast, the adapted context shows responses concentrated at lower levels.
4) **Accessibility**. In Q10 (difficulty in manipulating the environment), the responses in the unadapted context are significantly more dispersed, with a high median. This indicates that interacting with the environment was perceived as considerably more challenging in this context, whereas the adapted context was perceived as more manageable, with responses clustered at the lower end of the scale. Q11 (willingness to use the interactions) reflects a similar behaviour, suggesting that users would prefer to avoid these interactions in the unadapted context, compared to the adapted one.
5) **Fatigue and safety**. In Q14 (feeling of safety), the unadapted interactions show a higher median, indicating that users felt less safe in this context. The dispersion is also higher, suggesting that some users felt significantly less safe than others, particularly the more severely injured patients. Q19 (feeling of fatigue) shows a similar trend. This reinforces the perception that the unadapted context resulted in a greater physical and mental load for the users.
6) The remaining questions show no variability (Q1, Q16, Q17, Q18).

Additionally, we will check if there are significant differences between the responses to the questions that show variability using a Wilcoxon Signed-rank test [42]. This non-parametric test will be used instead of the t-test due to the non-continuous nature of the data obtained from the questionnaire, which is based on Likert-scale questions.

Except for questions Q12 and Q13, the p-value is significant as $p < \alpha, \alpha = 0.005$, indicating a statistically significant difference between the responses after using the adapted and unadapted interactions. Given the relatively small sample size and the need to ensure robustness in our statistical findings, we adopted a conservative significance threshold of 0.005 for the Wilcoxon signed-rank test. This choice aligns with best practices in studies with multiple comparisons, reducing the likelihood of false positives while maintaining confidence in the results. Observing the nature of the responses, we can affirm that users rated the adapted interactions significantly more positively.

Finally, we answer RQ3, as indicated in Section IV-A: *Do users positively evaluate the adapted interactions in terms of usability and user experience?* The statistical analysis of the questionnaire responses demonstrates that users, particularly the patients from HNPT, as can be seen from the individual responses available in the public repository, rated the adapted interactions positively. Thanks to this case study, we were also able to gain the acceptance of these patients and therapists regarding the use of these adapted interactions.

VI. CONCLUSION

In this paper, we have addressed the need to adapt hand interactions in immersive spaces based on Virtual Reality, aiming to improve accessibility for individuals with motor limitations. This proposal contributes to enhancing inclusivity in Virtual Reality, which is beginning to reach a maturity phase.

As a case study, VR Shopping was chosen. The number of people making their purchases online through a mobile device is increasing in an ever more digitalised society. VR Shopping is poised to be the next revolution in e-commerce, allowing users to have shopping experiences similar to physical ones, but from a distance.

Collaboration with the Hospital Nacional de Parapléjicos in Toledo has allowed us to evaluate the proposal in a real environment with individuals who suffer from real limitations, in this case, patients with spinal cord injuries and motor limitations in legs, arms, and hands. As observed in the results obtained, the adaptation of interaction mechanisms has enabled users to successfully complete tasks they could not finish with traditional mechanisms. This increase in effectiveness is accompanied by a reduction in effort around 40% and completion rates and time. While completion rates with adapted interactions are 100% for all users, completion times increase between a 3% and 91.6% depending on the tasks and interactions required. The average increase is 38.63% with a standard deviation of 32.84%, since the completion times significantly improves in tasks where hand shapes and specific positions are required and those more simple such as grabbing do not present such a high increase. Moreover, we hope that our metrics DI and ED can be used extended with other quantitative data for other purposes, i.e., fatigue muscle detection using signals from electrodes.

Besides quantitative evaluation, the proposal was also assessed qualitatively. We conducted a survey with questions from standard questionnaires including, NASA-TLX, System Usability Scale (SUS), User Experience Questionnaire (UEQ) and Motion Sickness Assesment Questionnaire (MSAQ), among others. This allowed us to assess how users perceived adapted interactions against unadapted ones. The responses to the questionnaire, based on Likert-scale questions, were analysed by using Wilcoxon Signed-rank test and boxplots. Wilcoxon p-values demonstrated significant differences among the responses given about adapted and unadapted interactions, being the adapted ones positively evaluated in terms of user experience, fatigue and usability, while unadapted ones where negatively evaluated. Moreover, among the volunteers that were patients the boxplots showed remarkable statistical differences among the responses given. The percentage difference among responses between adapted and unadapted interactions was 40.15%, with a standard deviation of 8.60%, considering all respondents.

Lastly, our intention is to continue to evolve the proposed solution. In future work, we will explore how to adapt more complex interaction mechanisms with hands in VR for individuals with mobility issues. In this way, we will explore how gesture recognition could work according to the limitations of each individual. Moreover, interactions with user interface for people with upper limb limitations were not researched. These interactions are crucial for interacting with VR applications. Therefore, we will make efforts to propose and evaluate solutions to adapt. Finally, in the context of VR Shopping as case study, we will research how VR shop layouts can be improved to make them more accessible, adapting not only interactions, but also the distribution of items, sections and shelves around a VR shop.

ACKNOWLEDGMENT

GPT-4o has been used for grammar enhancement.

DATA AVAILABILITY

All data collected during the experiment are publicly available in the GitHub repository: https://github.com/AIR-Research-Group-UCLM/VR-Hands-Interactions-Adapted. The repository is organized into two folders. One of them contains twelve folders, one for each of the users, containing all the data. The other, contains some Python code used to extract the information shown in the results section. The following Google Drive link contains a video showing the adapted interactions used in our case study https://github.com/AIR-Research-Group-UCLM/VR-Hands-Interactions-Adapted/blob/master/video_link.txt.

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