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Home-based mirror therapy in phantom limb pain treatment: the augmented humans framework

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Abstract

The "Augmented Humans" term refers to the opportunity to improve human possibilities by using innovative technologies such as Artificial Intelligence (AI) and Extended Reality (XR). Digital therapies, particularly suitable for those treatments requiring multiple sessions, are increasingly being adopted for home-based treatment, enabling continuous monitoring and rehabilitation for patients, thus alleviating the burden on healthcare facilities by facilitating remote therapy sessions and follow-up visits. Among these, the Mirror Therapy (MT) for patients suffering from Phantom Limb Pain (PLP) could benefit greatly. This paper proposes a novel "Augmented Humans" framework for the treatment of PLP through home-based MT; the framework is designed to consider the activities carried on by the therapy center, the patient, and the system supporting the treatment. Moreover, an XR-based solution that integrates a Deep Learning (DL) approach has been developed to provide patients with a self-testing and self-assessment tool for conducting at-home rehabilitation sessions independently, even in the absence of physical medical staff. The DL algorithm enables real-time monitoring of rehabilitation exercises and automatic provision of personalized feedback on the gesture's performance, supporting the progressive improvement of the patient's movements and his ability to adhere to the treatment plan. The technical feasibility and usability of the proposed framework have been evaluated with 23 healthy subjects, highlighting an overall positive user experience. Remarkable results were obtained in terms of automatic gesture evaluation, with macro averaged accuracy and F1-score of 95%, paving the way for the adoption of the "Augmented Humans" approach in the healthcare domain.

Keywords Augmented humans · Deep learning · Extended reality · Phantom limb pain · Home-based treatment · Augmented therapy · Digital therapy

1 Introduction

The practice of providing medical treatments and consultations through the internet using telecommunications technology is known as telemedicine [1]. This approach enables patients to connect with medical staff members like doctors, nurses, and experts without having to physically visit a hospital [2]. Additionally, telemedicine makes routine medical consultations

Extended author information available on the last page of the article

more convenient for patients [3], improving access to medical facilities and the effectiveness of healthcare for a large number of individuals. To enable virtual consultations, telemedicine involves a variety of communication techniques, such as video conferencing, phone conversations, secure messaging, and mobile apps [4]. Nonetheless, the digital technologies already available nowadays and the promising perspective of further development are promoting the adoption of an "Augmented Humans" approach to provide full support both from the physician and the patient's perspective fostering the improvement of the doctor-patient relationship and the therapy success [5].

The "Augmented Humans" paradigm aims to improve individuals' skills by making use of innovative technologies such as precision robotics, Internet-of-Things (IoT), Additive Manufacturing, but also Extended Reality (XR) and Artificial Intelligence (AI), whose recent increasing development is affecting multiple disciplines in the healthcare industry, such as orthopedics [6], urology [7], and oncology [8].

XR represents a continuum of technologies ranging from purely physical to entirely virtual reality, extending human perception through digital tools. XR includes three main categories of immersive technologies [9], which from the least immersive to the most immersive, are Augmented Reality (AR), in which digital information is superimposed on the real world, Mixed Reality (MR), in which virtual objects dynamically interact with the real world, and Virtual Reality (VR), in which the world that the user experience is entirely virtually generated. AI is a branch of computer science that deals with the development of systems and algorithms that can perform tasks that would normally require human intelligence [10], such as reasoning, learning, natural language understanding, image recognition, problem solving, and decision making. Specifically, machine learning (ML) is a subfield of AI that focuses on developing algorithms that allow systems to learn from data and improve their performance without being explicitly programmed for each task. Deep Learning (DL), a subcategory of ML, instead uses deep artificial neural networks to model complex data and make decisions or predictions.

In recent years, there has been a significant shift in healthcare paradigms towards more patient-centered approaches to treatment [11]. "Augmented Humans" proved to be core for the home-based treatment, which is at the forefront of this transformative shift, offering the opportunity to receive medical care, therapy, and rehabilitation within the comfort and familiarity of patients' own homes. Home-based treatments are a comprehensive range of medical and therapeutic services that are specifically tailored to meet each patient's individual needs, whether it be for managing chronic illnesses [12], recovering from surgery [13], getting palliative care [14], or even addressing mental health issues [15]. This approach to healthcare has gained prominence for several compelling reasons. Firstly, it promotes patients' autonomy, allowing individuals to actively participate in their care plans in such a way that therapies could fit with their preferences and lifestyles. Secondly, it reduces the burden on healthcare facilities, freeing up resources for more critical cases while making the therapy more easily accessible for those who may have difficulty traveling to a clinic or hospital. Additionally, home-based treatment provides the opportunity to receive treatment in a supportive and familiar environment, which can have a positive impact on a patient's emotional well-being and recovery process.

Phantom limb pain (PLP), a debilitating condition that affects individuals who have undergone amputation or experienced limb loss due to trauma or disease, turns out to be a breeding ground to adopt an "Augmented Humans" approach for improving the quality of the treatment. It is estimated that 80% of all the patients who underwent amputation report a sensation of a phantom limb and, additionally, PLP [16]; this percentage increases if children with congenital absence of limb are considered [17]. Amongst the therapeutic techniques employed in PLP treatment, mirror therapy (MT) plays a key role. MT involves the use of mirrors to create visual illusions that can help alleviate pain, improve motor function, and reduce sensory disturbances in the affected limb [18]. In 2009 Darnall et al. [19] reported a case study involving a patient with acquired above-knee amputation; his results with standard care were disappointing even though he was receiving multidisciplinary care for his condition. His agony from the phantom limb vanished once he started receiving self-delivered, home-based mirror treatment. Some years later, Darnall and Li [20] extended the study to forty patients confirming that the findings supported the efficacy of home-based self-delivered mirror therapy, also providing benefits in terms of costs; nonetheless, the authors highlighted the need to broaden further the investigation to people with lower levels of education to draw conclusions regarding the feasibility of such an approach. The advent of XR technologies allowed to employ both Virtual Reality (VR), such as Köktürk et al. [21], who carried out a virtual treatment deployed on an Oculus Rift, and Augmented Reality (AR), such as Thørgersen et al. [22], who demonstrated the suitability of the treatment on seven PLP patients superimposing the virtual 3D model of the limb to the missing one.

The paper is structured as follows: The next Section highlights the research objectives, Section 3 reports previous works related to the XR technologies employed in the PLP treatment and DL studies on Hand Gesture Recognition, which is core to automatically recognize hand movements during rehabilitation exercises; Section 4 describes the augmented framework and a demonstrative solution employing XR and DL according to the "Augmented Humans" paradigm; Section 5 shows and discusses the obtained results; Section 6 draws the conclusions.

2 Aim and goals

The goal of the current work is to outline a framework for the treatment of PLP through home-based Mirror Therapy according to the "Augmented Humans" approach. In this sense, patients are requested to perform exercises making use of XR technologies, while DL algorithms are integrated within the framework to verify the correctness of the performed exercises and provide real-time feedback. The framework is designed to support both the physician and the patient according to a user-centered perspective, considering of utmost importance the need for a medical expert for the whole treatment supervision and intervention in case of a critical situation. As most of the current solutions are tied to the requirement to perform rehabilitation exercises under the direct supervision of a healthcare specialist, digital tools are currently mostly used to improve patient awareness through better visualization or doctor-patient communication. To maximize the effectiveness of the therapeutic approach at home, the proposed framework integrates these features with a DL-based automated assessment tool to empower patients to self-test and self-assess their performance by supporting remote therapy sessions in which patients can perform the exercises at home without the constant need for the physical presence of medical staff. With the introduction of a DL-based algorithm for the identification of the correct rehabilitation exercise, patients can independently monitor their progress, receive immediate feedback, and adapt exercises accordingly, fostering a sense of autonomy and encouraging continued engagement in therapy. As an example of the feasibility of the proposed framework, an initial solution based on MR and DL technologies was designed and developed to conduct virtual MT sessions in a home environment, relying solely on a Mixed Reality (MR) Head-Mounted Display (HMD). Unlike other solutions that may depend on a wide range of additional devices, such as motion capture systems or specialized sensors, this approach simplifies the setup for the patient, making the proposed PLP home-based treatment highly accessible, and allowing patients to engage in effective therapy without the need to purchase or maintain expensive or complex equipment at home. The minimalist hardware requirement also makes the proposed solution more portable, increasing its potential for use in a variety of settings. The remote management of patient monitoring allows for continuous supervision of patient progress without the need for frequent in-person visits, enabling physicians to respond quickly when needed. Finally, the framework presents guidance for automatically generating detailed patient progress reports, which are shared with the medical team to facilitate timely adjustment of the treatment plan. This provides an efficient and transparent way to manage patient data, ensuring a complete and up-to-date understanding of their condition.

3 Related works

The framework presented in the current study aims to integrate XR and Deep Learning digital technologies for the home-based treatment of PLP.

Section 3.1 summarizes the recent employment of XR as a visualization technology capable of improving the patients' and the physicians' experience in the treatment of PLP. Section 3.2 gathers DL methodologies that have been adopted for Hand Gesture Recognition, which is core for the automatic verification of the exercises' correctness performed by the patients and the development of a truly user-centered solution.

3.1 Extended reality solutions for phantom limb pain

Among the first approaches to support PLP therapy using AR, Desmond et al. [23] implemented a solution to move a 3D arm representation on a screen through the data sent by a glove equipped with sensors that the patient could wear on the healthy hand. Similarly, Murray et al. [24] employed a HMD to display a virtual environment (VE). A glove was utilized for upper-limb participants to depict their limb movements, while sensors were used for lower-limb participants. For amputees with lower or upper limbs, sensors were attached to the knee and ankle joints or the elbow and wrist joints, respectively. In 2010 Georgoulis et al. [25] incorporated PLP in an innovative pain management system to deal with other two different kinds of pain, i.e., acute pain and chronic pain; pain relief was provided to the patients by showing AR scenarios triggered by analyzing facial expressions. Following a different approach, Huang et al. [26] carried out a study on hand phantom maps based on tactile sensory feedback and employing support vector machine (SVM) for the maps generation, while Henriksen et al. [27] provided electrical stimulation to amputees playing VR games and the patients affirmed to feel an increased control of the amputated limb in addition to pain relief, whereas Snow et al. [28] presented a case-study proving a 50% pain reduction and increased mobility of the amputated limb by means of a VR headset, Oculus Rift, and haptic feedback.

Several works focused on the use of myoelectric signals to map healthy limb movements. A myoelectric virtual hand is a sophisticated prosthetic device that uses myoelectric signals generated by the residual muscles in an amputee's residual limb to control the movements of the prosthetic hand. The virtual hand can be displayed using desktop VR [29–31], HMD VR [32–34] and MR [35–37], helping to relieve pain in the vast majority of patients who underwent the experiments. Likewise, the same approach can be also adopted for the treatment of lower limbs, as shown by Correa-Agudelo et al. [38] in their study related to amputated victims due to anti-personnel mines in Colombia, and by Zeher et al. [39] in their program conducted by the Defense Advanced Research Projects Agency (DARPA) to implement a platform to design, develop and test prosthesis through a strict interaction between patients and physicians.

The above-mentioned works found evidence of an improvement in terms of pain relief in amputees experiencing PLP. These findings fostered the development of solutions employing XR technologies coupled with motion tracking systems to better focus on the specific movements requested for the rehabilitation. Several works focused on the realization of "exergames", aiming to blend the higher entertainment level provided by a game with exercises targeted for rehabilitation [40]. In this sense, the Microsoft Kinect market entry, followed by other customer-grade motion capture systems such as Leap Motion [41], enabled a fast and accurate tracking propaedeutic to virtual models animation, as shown by Carrino et al. [42], Fukumori et al. [43], and Penelle et al. [44]. Actually, Inamura et al. [45] used the spatial information provided by Kinect v2 to animate a virtual avatar and adapt the arm length to the user's one, increasing the sense of agency and sense of ownership, even if the experiment was limited to healthy subjects. More recently, Adaikkammai et al. [46] designed a solution including a motion-sensing glove to send real-time data to a virtual environment by means of an Arduino microcontroller and a motion tracking device. Another example of adaptation was provided by Annaswamy et al. [47], through the development of a MR application (Mr. MAPP) capable of real-time capture and generation of a 3D model of the patient's healthy arm to overcome the dependency on pre-built 3D models which, according to the authors' opinion, could negatively affect the overall experience; the same authors presented a modified version of Mr. MAPP for the lower limbs treatment [48] and taken up by Chung et al. [49] in order to further increase the sense of experience perceived by the user.

Eventually, motion capture systems proved to be useful to trigger non-visual feedback, such as auditory and tactile sensations [50, 51], or artificial upper limb movements [52], as evidenced by the Nervebot solution [53], that can be controlled via the internet in a shared near-real virtual environment. The importance of patient's comfort during the virtual experience was investigated by Nielsen et al. [54], who compared two different positions to perform rehabilitation exercises, i.e., sitting and lying, finding that the results were strictly exercise-dependant and suggesting that VR-based approach might be preferable to easily adapt the exercise setup to the patients' needs, as well as by Henriksen et al. [40] with their study focused on anti-symmetrical movements, like walking, running, and cycling.

Although traditional desktop or personal devices have advantages in terms of ease of use [55], the spreading of HMDs definitely fostered the employment of XR as enabling technology to support and study PLP. Thørgersen et al. [22] designed an innovative MR solution consisting of an Oculus Rift equipped with two additional digital cameras in order to simulate the arm amputation by removing own-limb visual feedback; Carrino et al. [56] presented IMPACT, a platform equipped with Oculus Rift, OVRvision Pro stereo cameras, and Kinect v2 implementing customizable serious games; similarly, Osumi et al. developed an Oculus Rift application integrated with infrared stereoscopic cameras, both Kinect v2 and Leap Motion, to track the movement of the healthy limb [57]; Köktürk et al. [21] provided a twofold solution, LIMBrehabVR, available for smartphone or Oculus Rift designed to potentially reach double-limb amputees; Akbulut et al. [58] integrated Kinect, Oculus Rift, and a wearable surface EMG sensor in a pilot study consisting of four different serious games, and the solution was considered practically suitable for usage without physician's assistance; for the same purpose, Marsh et al. [59] proposed a framework including Oculus Go and computing the virtual arm position and orientation using an inverse kinematics model; Saito et al. [60] used an optical see-through HMD, the Microsoft HoloLens, and the Leap Motion infrared camera to properly project the image of the phantom hand in front of the patient's field of view, extending the solution into a shared VR space in a subsequent work using the Oculus Rift [61]; the same hardware usage was employed by Kocur et al. [62] to specifically focus their study on missing fingers and obtaining promising responses according to the involved patients. Even more complex visualization systems have been used to make the experience totally immersive, such as the adapted CAVE-like projection employed by Molla et al. [63] that, coupled with a motion capture system, allowed the user to control a virtual avatar and maximize the patient's full-body awareness.

Recently, several studies have been conducted on PLP home-based rehabilitation treatments based on XR technologies, obtaining promising results in terms of adherence to therapy, pain relief, and improved functions and balance [64–66]. For example, Tong et al. [67] reported in a case series that immersive VR experiences provided significant relief from PLP, with patients reporting a dreamlike sensation of moving their limbs, underscoring the potential of VR to alter perceptual experiences in amputees. Additionally, Abbas et al. [68] conducted a randomized, controlled trial to examine the impact of adding VR to traditional exercise programs for unilateral traumatic lower extremity amputees, demonstrating that VR not only significantly reduces pain, but that incorporating VR into rehabilitation can offer significant psychological benefits to PLP patients. Other researchers, such as Lendaro et al. [69], have focused on enabling patients to take control of their own rehabilitation while maintaining supervision of the attending medical staff through telemedicine platforms. In their work [70], they exploit myoelectric pattern recognition based on machine learning algorithms to decode motor intentions from the stump muscles in order to use them to command certain virtual environments, thus providing adaptive therapy and improving home rehabilitation.

The carried-out analysis highlighted the importance of identifying a trade-off to combine the importance of providing reliable results in terms of accuracy for the correct gesture assessment and the need for an agile, easy-to-use solution to support the exercise execution in a home environment, even without the presence of medical staff.

Table 1 summarizes the results of the literature review on XR-based solutions for PLP rehabilitation therapy. Each paper has been categorized according to the XR technology used, the type of XR device employed, the type of tracking exploited for the healthy limb, and the need for additional cameras and/or wearable sensors to complete the setup. In addition, the last column of the table refers to whether some type of feedback can be provided to the user for the eventual therapy adaptation or personalization.

To the best of our knowledge, this is the first work that integrates a DL algorithm into an XR solution to offer an automated self-assessment and self-monitoring tool for supporting patients during remote therapy sessions without requiring physical medical staff involvement. The DL-based algorithm allows real-time monitoring of the execution of rehabilitation exercises, checking their correctness in execution, and providing automatic feedback on the execution. This supports the patient's progressive improvement of their phantom limb pain and their ability to adhere to the treatment plan, ensuring a successful and safe rehabilitation at home. Furthermore, this MR HMD-only approach further simplifies the patient setup compared to other solutions that might rely on a variety of additional devices, like motion capture systems or wearable sensors.

Table 1 Summary of current solutions that employ XR technologies in PLP rehabilitation therapy, with reference to the XR technology and devices used, healthy hand tracking type, additional cameras and sensors needed for the setup, and the eventual possibility of therapy adaptation or personalization

Authors	XR Technology	XR Device	Healthy hand Tracking Type	Additional Cameras	Additional Wearable sensors	Personalization/ Adaptation
[23]	AR	Desktop	outside-in	NO	YES	None
[44]	AR	Desktop	outside-in	YES	NO	None
[38]	AR	Desktop	outside-in	YES	YES	None
[35–37]	AR	HMD	outside-in	NO	YES	None
[25]	AR	HMD	outside-in	NO	YES	Biofeedback dynamically changed based on face expression analysis
[47–49, 60]	AR	HMD	outside-in	YES	NO	None
[29–31, 39, 43, 55]	VR	Desktop	outside-in	NO	YES	None
[53]	VR	Desktop	outside-in	YES	YES	None
[69, 70]	VR	Desktop	outside-in	YES	YES	Therapy adaptation based on EMG stump residual muscle activity
[21, 24, 32, 33]	VR	HMD	outside-in	NO	YES	None
[27, 28]	VR	HMD	outside-in	NO	YES	Haptic feedback provided through haptic sensors
[22, 41, 42, 45, 61, 62, 64, 65]	VR	HMD	outside-in	YES	NO	None
[34, 56, 58]	VR	HMD	outside-in	YES	YES	None
[46, 50–52]	VR	HMD	outside-in	YES	YES	Haptic feedback provided through haptic sensors
[40, 54, 59, 66, 67]	VR	HMD	inside-out	NO	YES	None
[63]	VR	CAVE	outside-in	YES	YES	None

3.2 Deep learning solutions for hand gesture recognition

The rapid development of artificial intelligence approaches in computer vision led to the adoption of deep learning-based methods, which demonstrated to provide state-of-the-art results thanks to their ability to automatically learn hierarchical representations from data [71]. Since hand gesture recognition interprets and understands human hand movement through the use of computer vision, the rising popularity of deep learning had an impact on multiple domains, such as surgery [72], reading assistant systems for blind people [73], sign language translation [74], art [75], computer games [76], smart homes [77], human-computer [78], and human-robot interaction [79]. Among the existing DL approaches used for addressing hand gesture recognition, those leveraging hand keypoints identification rather than the whole input image or frames from a video were considered. Indeed, the literature highlights that keypoint-based hand gesture recognition methods are more appropriate to minimize the complexity of the system to provide real-time results and keep the focus on the hand movement, avoiding possible sources of confusion arising from original image visual features, for example, the image background, camera viewpoints, or unfavorable lighting conditions [78, 80–82].

DL-based hand gesture recognition systems commonly adopt a two-step design. The first stage consists of a hand-keypoint estimation model serving as a feature extractor; the second stage includes a further deep-learning model to infer the hand gesture class. The most significant differences among the methodologies usually arise in the latter stage. Lu et al. [73] involved hand keypoints for training a simple classifier to save computing power for reading assistance for blind people purpose. Following the same idea, Neog et al. [83] leveraged on VGG16 network to infer the classification labels from hand keypoints. A simple and effective hand gesture recognition system was proposed by Xie et al. [84] to enable high-accuracy real-time gesture recognition on embedded devices with limited processing power. A cascaded multi-task convolutional neural network was implemented to simultaneously predict hand detection probabilities and regress hand keypoint positions. An adaptation of this neural network has been proposed to find a trade-off between the required computational power and the need to consider the temporal component. Zuo et al. [74] proposed to guide a spatial attention module through pre-extracted pose keypoints heatmaps to focus on informative regions. Furthermore, they introduced a sentence-level consistency constraint between the visual and sequential features to improve the performance of continuous sign language recognition. Additionally, a further module comprising a transformer, an LSTM block, and a fully connected block was added to the system in order to encode the temporal correlation information and estimate the gesture category. Wang et al. [72] presented a novel Human-Robot Interface to achieve touch-free and precise manipulation with a surgical robot in robot-assisted minimally invasive surgery. The system was based on a UNet architecture to address gesture recognition, leveraging hand-keypoint regression and hand-shape reconstruction methods. Avola et al. [85] proposed a new framework for 3D hand pose and shape estimation, which was extended for addressing gesture classification by adding the same classifier described in [86]. In the same year a vision-based multi-input fusion deep network (MIFD-Net) was introduced by Wang et al. [78]; first, hand keypoint data and gesture images were processed through Euclidean distance normalization and image segmentation technologies; then, both the information for gesture classification were fused.

Literature showed that single frames are typically used as input for the designed neural networks, especially due to the higher computational power required to analyze videos. Nonetheless, within the augmented framework that the current work is going to propose, relying on temporal application is crucial to correctly assess the rehabilitation exercises and provide actual support to the patient during the exercise performance. Temporal information can be analyzed without considering the whole image or frame, but relying on hand keypoints, thus reducing the input data size. Therefore, it has been chosen to rely on hand keypoint coordinates in order to feed an LSTM neural network architecture.

The Long Short-Term Memory (LSTM) architecture is highly effective for capturing temporal dependencies in data, making it particularly advantageous for tasks that require understanding sequences of information [87]. Unlike other machine learning and deep learning approaches, such as Convolutional Neural Networks (CNNs) that excel at processing spatial features in static frames [88], LSTMs are specifically designed to handle time-based patterns. This makes them ideal for applications like rehabilitation exercise assessment and hand gesture recognition, where movements unfold over time. In these scenarios, many gestures, letters, or words are dynamic and cannot be accurately recognized by analyzing individual frames in isolation. LSTMs, however, can track the sequential progression of these actions, ensuring that the temporal information is incorporated into the analysis. This capability enables LSTM-based systems to recognize complex patterns of movement that might otherwise go undetected, providing a significant edge over other architectures that do not account for the importance of time [89]. By maintaining and utilizing memory of previous inputs, LSTMs can interpret not only the current state but also the context in which it occurs, leading to more accurate and robust performance in dynamic environments.

A detailed description of the employed dataset, the network architecture, and training parameters is provided in Section 4.3.

4 Methods

As highlighted in the previous Sections, wide adoption of digital technologies has spread in the rehabilitation processes with a particular focus on PLP. These tools broaden the spectrum of possibilities to realize therapies tailored to the patients' needs according to a "patient-centered" approach. Nonetheless, current solutions are intertwined with the need to perform rehabilitation exercises under the direct supervision of a therapist; thus, digital tools are employed to enhance patients' awareness through enhanced visualization or improved physician-patient communication. The proposed framework aims to integrate these features with an automatic assessment tool to further exploit the home-based treatment approach by letting patients' perform exercises autonomously, without the need for ongoing physical medical care.

Figure 1 illustrates the activity diagram for the entire framework and lists the tasks that the patient, the system, or the therapy center must perform in order to complete the whole procedure. This Section is organized as follows: subsection 4.1 describes the proposed framework, while subsections (4.2 and 4.3) clarify the role of MR and DL technologies through the description of an innovative solution for PLP exercises performance and assessment.

4.1 Augmented framework

Three prerequisites must be sequentially met by each patient to activate digital therapy for the home-based treatment of PLP.

1. Patient's health condition. This evaluation performed by the healthcare operator takes into account a number of variables, including the patient's overall health, the degree and kind of PLP, the patient's mental and physical capability to adhere to the therapy at home and any other concerns that could compromise the treatment's safety.

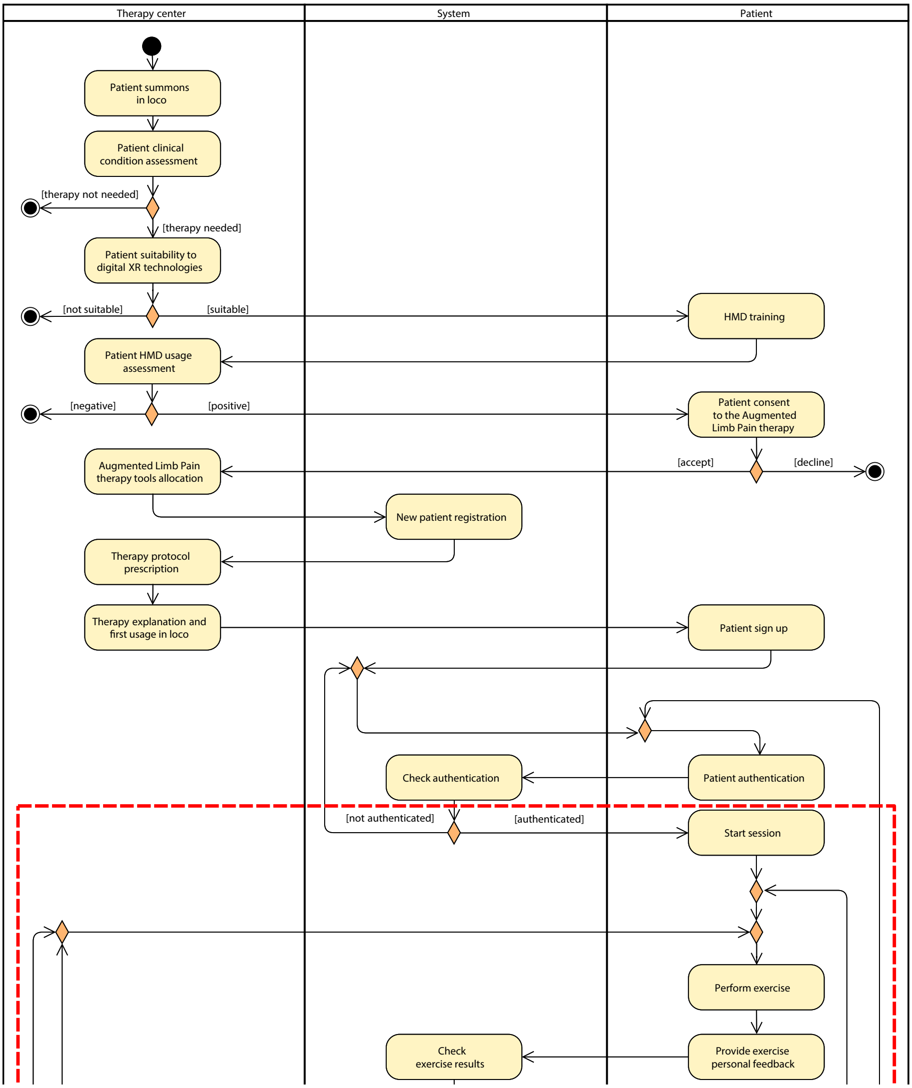


Fig. 1 PLP home-based Mirror Therapy treatment framework activity diagram. The activity diagram outlines the actions that the patient, the system, or the therapy center must do for the telemedicine operation to be completed. The red dashed rectangle identifies the framework area on which the solution proposed in Section 4.2 and Section 4.3 is focused on

2. Patient's attitude in using digital technologies. A licensed healthcare operator should train the patient on how to use the device properly during this phase and evaluate his capacity to manage the HMD safely. Training must cover how to use the HMD, including how to put it on correctly, switch it on, and navigate the interface, as well as how to handle any technical issues that could come up while using it.
3. Patient's willingness to undergo a digital therapy treatment. The patient's dedication and active engagement are necessary for home-based treatment in order to execute MT

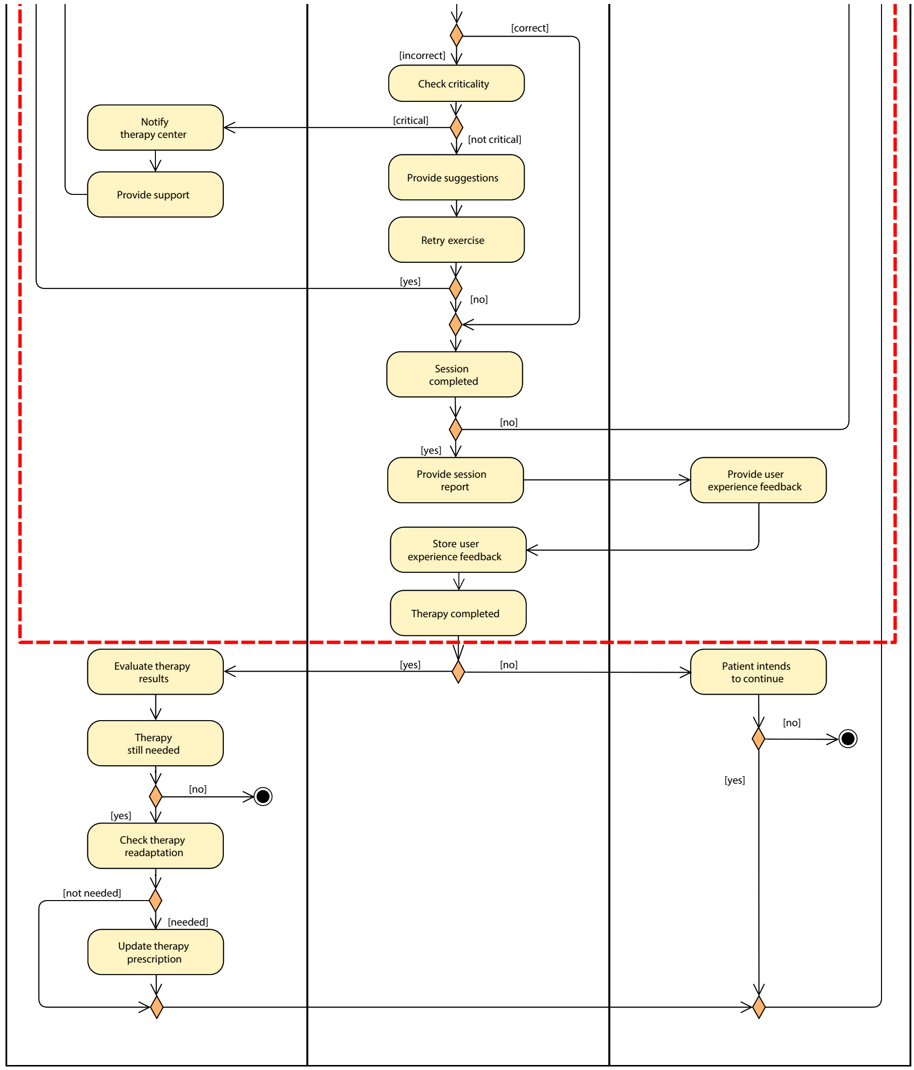


Fig. 1 continued

exercises on a regular basis, adhere to the application instructions, and offer information and comments during augmented therapy sessions.

If the patient meets the above-mentioned requirements, the therapy center will register the patient for the telemedicine service and assign the required tools for the augmented therapy. This ensures that the patient is fully equipped to conduct the home-based treatment without the need to independently purchase any hardware or software. Personal information, informed permission for treatment participation, and acceptance of the telemedicine application's terms of use may all be sought during the registration process.

The therapy center can then provide a therapy prescription, taking into consideration the patient's special needs and personal responses to treatment. The therapy prescription will consist of specific information, including the frequency of sessions, length of the period of treatment, exercises to be carried out, therapeutic objectives to be met, eventual patient progress monitoring, and regular follow-up appointments.

A first on-site therapy session will be arranged in order to provide the patient with the knowledge to deal with augmented therapy independently. During the first session, the patient will learn about the HMD device and execute some virtual mirror exercises while being observed by a healthcare operator, who can explain therapy prescription details, and address any queries or worries the patient may have. To enhance accessibility and ensure that all patients can fully benefit from the therapy, training will be customized to meet each individual's specific needs. This tailored approach will take into consideration various factors, such as the patient's prior experience with technology, cognitive capabilities, and any physical limitations they may have. By adapting the training to these individual characteristics, we aim to simplify the technical aspects and make the therapy more approachable for all patients, regardless of their level of familiarity with digital tools. This personalization will not only ease the learning curve but also empower patients to confidently engage in their rehabilitation process. Moreover, by reducing potential barriers related to technology use, this approach is expected to foster a more positive attitude toward digital technologies, encouraging patients to embrace these tools as integral components of their rehabilitation program. Ultimately, this strategy seeks to optimize patient participation and enhance the overall effectiveness of the therapy.

During the first home therapy session, the patient enrolls in the app, establishing the credentials required for login and future access. The patient can launch the app on the HMD supplied by the medical center and log in with the personal credentials to start a therapy session. The treatment session can be started only if the system detects a patient who has been medically cleared for treatment by the medical center.

Within the application, the patient has the option to choose from a series of virtual mirror therapy exercises, those predetermined by his treatment prescription.

The patient is requested to give comments regarding the exercises after completing each activity (Fig. 2). The patient's performance during the execution of the exercise, such as running time and correctness of the performance, are evaluated, along with user feedback, to

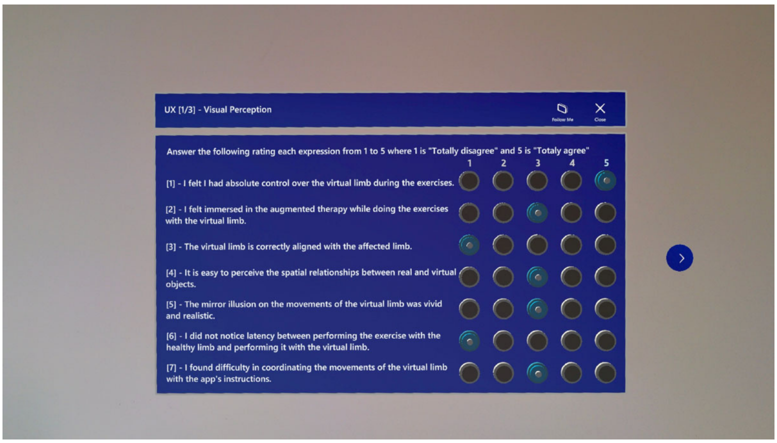


Fig. 2 MR solution scene views captured from HoloLens 2 word-facing camera while completing self-evaluation test

provide execution suggestions to the patient, or in case of a critical situation, alert the therapy center to start a real-time remote support procedure.

If the digital therapy is completed, the gathered information is combined into a report containing exercise evaluation and user feedback, which is requested to provide comments on the overall user experience that the system can store for later use, for instance for further development of the app. The digital therapy can be stopped by the user at any time.

The medical facility gets the sent data at the conclusion of therapy and carefully assesses it to track the patient's development during PLP treatment. The treatment plan may need to be modified based on the assessments or, maybe, the patient's willingness to continue therapy. For example, new exercises may be added or current ones modified, and the length or frequency of therapy sessions may be changed.

In the following Sections (4.2 and 4.3) a solution compliant with the described framework has been proposed. Although the framework describes the overall workflow from the very first medical examination, in which the need for a rehabilitation path arises, to the whole digital therapy completion, the solution focuses on the methodological perspective that allows for the adoption of the "Augmented Humans" paradigm. In fact, as highlighted in Fig. 1, the framework blocks involved in the proposed solution are those describing a single digital therapy session, namely those enabling a truly remote rehabilitation. It has been decided not to include the other blocks in the experimentation, because they would have lengthened the paper not providing innovative content.

A physiatrist expert in PLP treatment participated in the exercise definition and the automatic hand gesture recognition evaluation.

4.2 Mixed reality-based solution

MR allows for the integration of reality with virtual content with which the user can interact. The ability to share clinical data, medical reports, and audio-video connected to the patient in real-time throughout the whole procedure must always be guaranteed.

In this context, a MR-based solution that allows patients to conduct virtual MT sessions in their home environment, using only a MR HMD, has been developed.

The application's main objective is to promote the patient's autonomy in the rehabilitation process to manage the therapy without the need for on-site medical staff. This is accomplished by giving the patient a self-testing and self-assessment tool to conduct rehabilitation sessions at home independently, thanks to the possibility of receiving real-time virtual visual feedback from a first-person perspective while performing perceptual exercises. In this way, it is possible to reverse the maladaptive plasticity of the sensorimotor brain and relieve pain by increasing the mobility of the phantom limb [90]. Additionally, using a virtual prosthesis model encourages adaptation to the real prosthesis and a sense of familiarity and acceptance of it, creating continuity in therapy once training is finished [91].

An animated human hand model depicts the exercise in the proper way to aid in reproduction by the patient, providing a real-time visual guide to assist the patient in performing the exercises correctly. Opening/closing of the fist, thumb-to-finger opposition, and flexion/extension of the thumb were the implemented motor tasks. The patient is then asked to perform the exercises with both the intact and residual limbs at the same time. The movements of the intact hand are tracked and mirrored in real-time on the virtual prosthetic model overlapped to the patient's stump, giving him the illusion of performing the exercise independently on the virtual limb. Deep learning feedback is immediately provided to the patient to indicate whether the exercise was performed correctly, allowing for patient self-assessment.

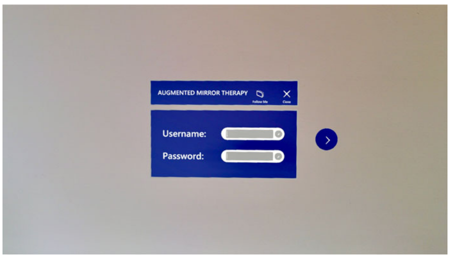
The MR application workflow can be summarized as follows:

1. the patient puts on the headset, and logs in to his therapy session (Fig. 3);
2. a virtual model of a prosthetic limb is overlapped on the residual limb to give him the illusion of wearing a real prosthesis;
3. using a push-button menu, the patient can select the exercises specified in his therapy plan from a variety of options;
4. the rigged model of a human hand is used to recreate the proposed exercise;
5. the patient performs the exercise with both the intact and residual limbs;
6. the movements of the healthy limb are tracked and mirrored in real-time on the virtual prosthetic model;
7. the patient receives instant deep-learning feedback indicating if the exercise was carried out properly (Fig. 4).

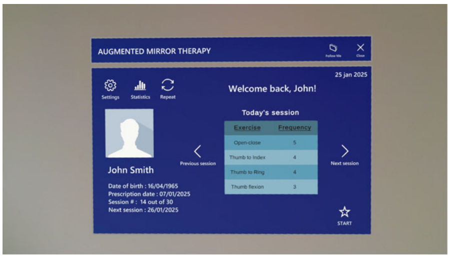
The Microsoft HoloLens (HoloLens, Microsoft, Redmond, WA, USA) was chosen as the HMD due to its unique characteristics as a commercially available optical-see-through device with a self-sufficient computer power source and wireless connection. The MR application was developed using the cross-platform game engine Unity3D (v2021.3.18f1) and integrated with the Mixed Reality ToolKit (MRTK) to support user interactions within the application. The MRTK framework provides a series of components primarily designed for the development of MR applications, which comprises hand gesture detection, head movement tracking, and voice command recognition capabilities.

An 80 mm square marker is worn on the patient stump to properly identify the user's arm, and superimpose the virtual model accordingly positioned and oriented. To that purpose, the detection and tracking capabilities of Image Targets supplied by the Vuforia SDK were included in the MR application. Image Targets are images that the Vuforia Engine detects and tracks in real-time by recognizing naturally occurring features in images. These extracted image features are stored in a preprocessed database, which is then integrated into the software application and used for runtime comparisons. Vuforia Engine tracking will continue as long as the Image Target is at least partially visible to the camera after recognition.

The healthy limb's movement is tracked using the Microsoft HoloLens 2 inside-out hand tracking system, detecting the coordinates of the supported tracked hand joints. The detected coordinates are then mirrored on the sagittal plane and remapped onto the corresponding joints of the virtual prosthesis model; in this way, the movement is reproduced on the affected limb, and virtual visual feedback is provided to the patient on the movement that has been performed.

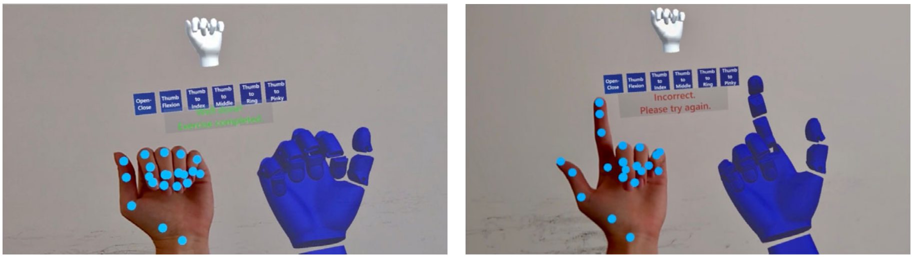


(a) Log in screen



(b) Application home screen

Fig. 3 MR solution scene views captured from HoloLens 2 word-facing camera at login in the application



(a) Exercise performed correctly (b) Exercise performed incorrectly

Fig. 4 MR solution scene views captured from HoloLens 2 word-facing camera during a therapy session

4.3 Deep learning-based methodology for virtual mirror therapy assessment

The exercise assessment during the remote therapy session was addressed by a keypoint-based LSTM architecture for Hand Gesture Recognition. The general workflow, shown in Fig. 5, includes a keypoint estimation and an LSTM-based action recognition step. The system receives in input the frames related to the current exercise, Microsoft HoloLens 2 inside-out hand tracking system was used to track the motion of the healthy limb, identifying the coordinates of the supported tracked hand joints, and serving as a feature extractor of the LSTM Hand Gesture Recognition model, which was handled as a classification task and provided the predicted executed exercise as output. The dataset, the model architecture, and the training process are described in the following subsections.

4.3.1 Dataset

The LSTM network was trained with a custom dataset that comprised video data for each rehabilitation exercise and the corresponding keypoint annotations. Six exercises were considered as examples for the current investigation:

1. Closing of the fist
2. Flexion and extension of the thumb
3. Thumb to index finger opposition
4. Thumb to middle finger opposition
5. Thumb to ring finger opposition
6. Thumb to pinky opposition

For each class, 60 videos were recorded reproducing the movement for the specific gesture. In addition, a neutral class was created to collect random gestures related to exercises not included in the therapy. Thus, the comprehensive dataset consisted of 420 videos, of which 10% were randomly selected to produce the test set. As a result, the final dataset comprised 357 videos for training, and 42 for test sets, respectively.

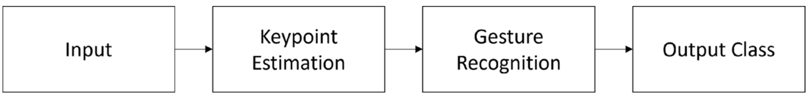


Fig. 5 General workflow of the Hand Gesture Recognition process

Video data should be provided in the form of a set of hand keypoints coordinates along with their associated gesture label to train the LSTM network for hand gesture detection. The Google MediaPipe framework [92] was employed as a data annotator for this purpose. MediaPipe takes advantage of machine learning pipelines to handle time series data, including audio, video, and text. It offers a collection of libraries with the ability to carry out various operations like object recognition, image classification, image segmentation, hand gesture recognition, hand landmarks, and pose detection.

The keypoint coordinates for each frame were estimated using the MediaPipe Hand Landmarker task [93]. Within the designated hand areas, the MediaPipe hand landmark model identifies 21 palm-knuckle keypoints, which are highlighted in Fig. 6 as blue points. Each keypoint is represented as a set of x, y, and z coordinates in a three-dimensional space.

The final application used the Microsoft HoloLens 2 inside-out tracking, which includes four additional metacarpal keypoints than the 21 provided by MediaPipe (shown by red points in Fig. 6). Nevertheless, the inference phase of the model did not include them for the hand gesture recognition phase because they were unrelated to the current gesture identification.

4.3.2 LSTM network architecture

Figure 7 illustrates the Long Short-Term Memory (LSTM) network architecture.

The network input is a set of triplets representing the x, y, and z coordinates of 21 keypoints belonging to each frame. A temporal sequence of 2 seconds was involved. Since the frequency was 30 frames per second, each input sequence comprised 60 frames. The model is composed of an LSTM block which extracts a significant representation of the input over time, and a fully connected block which provides the prediction. The former comprises five LSTM layers with 64, 128, or 256 output nodes, while the latter includes three fully connected and time-distributed Dense layers with 128, 64, and 32 output nodes, respectively, each followed by a Dropout layer with a probability of 0.4 of the input units to drop, to prevent overfitting. As an activation function, a rectified linear unit (ReLU) is placed after each layer of both blocks. In the final Dense layer of the architecture, a Softmax activation function is employed to map the 32 output units from the layer preceding to a probability function of the desired number of classes, which in this case is 7, consisting of six classes for example treatment exercises and the neutral class.

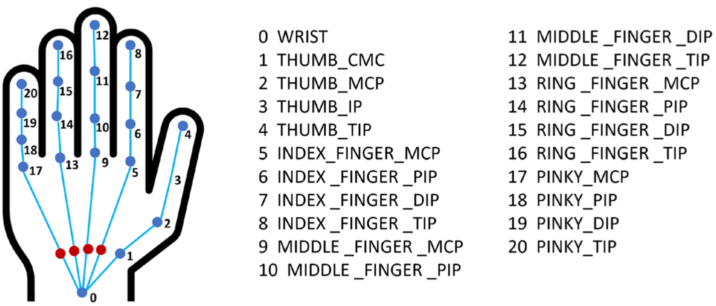


Fig. 6 21 MediaPipe landmarks (blue points), and four additional Microsoft HoloLens 2 metacarpal keypoints (red points)

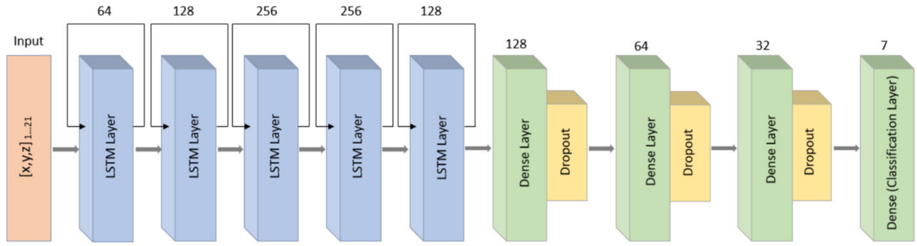


Fig. 7 LSTM network architecture. The input consists of a collection of triplets that represent the x, y, and z coordinates of each frame's 21 keypoints. LSTM layers are shown in blue boxes, Dense layers in green boxes, and Dropout layers in yellow boxes. Each box has a number on the top indicating the number of hidden units in the output space. Several output units equal to the classes to be discriminated are provided by the final layer

4.3.3 Training and metrics

The LSTM network architecture was trained for 121 epochs using an Adam optimizer with a learning rate of 0,0001. For parameter optimization, categorical cross-entropy and accuracy were chosen. The model ran for about 30 minutes on the Google Colaboratory platform, adopting the TensorFlow open-source machine learning framework and Keras API.

The classification performance of the LSTM network model was assessed by computing the confusion matrix and the related classification metrics, namely, accuracy, precision, recall, and f1-score, described below. Given the values of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), accuracy, precision, and recall are defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

The f1-score is defined as the harmonic mean between precision and recall and it is computed as:

$$F1 = 2 * \frac{precision * recall}{precision + recall}$$

The f1-score serves as a performance indicator by combining both measurements through harmonic mean since the relationship between precision and recall has an inverse proportion. Accuracy, precision, recall, and f1-score metrics were computed independently for each class and then they were macro-averaged to provide a more concise overview of the performance.

5 Results and discussion

In this paper, we provide a novel augmented framework with an "Augmented Humans" approach for the home-based treatment of Phantom Limb Pain through digital therapy. By offering patients a highly customized, enjoyable, and convenient home-based therapy option, this framework aims to provide a successful and efficient alternative to enable PLP patients to manage their rehabilitation minimizing the need for ongoing physical medical care.

5.1 User experience assessment

Twenty-six healthy subjects (ten male, thirteen female), aged 22 to 56 years old were selected through a public call for volunteers at Politecnico di Torino (Torino, Italy) to provide a first evaluation of the usability of the proposed MR solution. Participants were recruited from among those who have no previous experience with XR technologies. The sample size has been chosen by means of a power analysis performed considering a large effect size (0.8), a significance level of 0.05, and power of 0.8.

To provide a safe and obstacle-free environment for participants, a 2-by-2-meter section of our research lab has been designated as the testing area. Upon arrival, each participant needed to complete a consent form stating their willingness to engage in the study, as well as a demographic form containing basic demographic details such as age, gender, and any relevant background information. Participants were then briefed on the study's aims and procedures, including a full explanation of the experiment's scope, as well as a description of the HoloLens 2 headset's primary functions. Prior to testing, each participant conducted an eye calibration using Microsoft's Eye Tracking Calibration tool to calibrate the HoloLens eye tracking in order to properly capture the user's gaze and eye movements inside the MR environment. This ensures that the MR solution properly responds to the specific user's visual cues. After that, each participant went through a Hololens native training program (Learn Gestures by Microsoft) to learn how to interact with the holograms via head movements, gestures, and spoken commands. This training is critical for ensuring that users are proficient in utilizing MR technology and can efficiently explore and interact with holograms, thus avoiding bias due to unfamiliarity with the technology. Following calibration and training, the MR application is launched, and the subject engages in a complete session of therapy and interacts with the MR content.

At the end of the MR session, a questionnaire was distributed to participants to measure user experience (UX) related to visual perception, interaction and ergonomics, and engagement. As the questionnaire is not tailored to a specific condition or demography, it provides a more generalized understanding of how users from varied backgrounds and conditions perceive and interact with the MR solution.

The questionnaire, as shown in Table 2, consists of 20 items, each of which is scored on a Likert 5-point scale (from 1 "strongly disagree" to 5 "strongly agree"). The items express both positive and negative thoughts towards a given feature of our MR solution. Participants are asked to indicate their level of agreement or disagreement with the statement for each item. The questionnaire was drafted with both positive (affirmative sentences) and negative (negative sentences) items in mind. Favorable (Affirmative) items are statements that elicit a favorable response from participants: a high score on the Likert scale, such as 5, would indicate agreement or a favorable experience. Unfavorable (Negative) items are statements that elicit unfavorable responses from individuals: a high score might imply disagreement or an unpleasant experience. To make all items comparable, the negative sentences were reversed in the data analysis phase, such that a high score (5) was associated with a positive feature for our study.

With respect to the questionnaire results, the median was used to characterize the central trends of replies to a single test item, with dispersion determined by examining minimum and maximum values.

According to the data, the majority of users seem to have responded favorably to the statements. In general, our findings indicate that the solution was successful in providing a sense of visual control (median 4), allowing users to experience a high level of visual immersion in the virtual therapy environment (median 5), and effectively creating a good

Table 2 User testing questions for MR-based solution user experience evaluation

	Item	Questionnaire Items	Median	Min	Max
Visual perception	1	I felt I had absolute control over the virtual limb during the exercises.	4	3	5
	2	I felt immersed in the augmented therapy while doing the exercises with the virtual limb.	5	3	5
	3	The virtual limb is correctly aligned with the affected limb.	4	2	5
	4	It is easy to perceive the spatial relationships between real and virtual objects.	4	3	5
	5	The mirror illusion on the movements of the virtual limb was vivid and realistic.	4	1	5
	6	I did not notice latency between performing the exercise with the healthy limb and performing it with the virtual limb.	5	4	5
	7 *	I found difficulty in coordinating the movements of the virtual limb with the app's instructions.	5 (1)	2 (4)	5 (1)
Interaction and ergonomics	8	The field of view (FOV) is adequate for the application.	3	1	4
	9	I did not experience any postural discomfort during the application.	3	2	5
	10	I did not experience any visual fatigue.	3	1	5
	11 *	I experienced nausea and dizziness while using the application.	5 (1)	1 (5)	5 (1)
	12 *	I noticed a headache while doing the exercises or just after.	4 (2)	1 (5)	5 (1)
	13	Gesture interaction is simple and intuitive.	5	2	5
	14	The hand motion simulation is simple to follow.	5	3	5
	15	I used the app interface without any issues.	4	2	5
	16	No interruptions or technical issues occurred while I was using the application.	5	3	5
Engagement	17	I was able to perform the exercises successfully (personal performance).	5	2	5

Table 2 continued

Item	Questionnaire Items	Median	Min	Max
18 *	I put a lot of effort into reaching my performance level (effort).	5 (1)	4 (2)	5 (1)
19	The performance of the exercises is engaging (engagement).	5	4	5
20	I did not experience any feelings of insecurity, discouragement, annoyance, tension, or irritation while doing the exercises (frustration).	4	1	5

The sign "*" was used to highlight negative sentences in the "Item" column. The aggregate questionnaire results were provided in terms of median, minimum value, and maximum value. The reversed values have been reported for the negative sentences, while the real values are indicated in parentheses visual illusion of the mirror (median 4), allowing proper alignment of the virtual prosthesis (median 4), with no noticeable visual delays between the performance of exercises on the healthy limb and virtual limb (median 5).

In terms of interaction, the majority of users report that the gesture interaction and app UI were perceived as user-friendly and intuitive (median 5 and 4), and they were able to complete their experience without incident (median 5), indicating strong usability for the interaction. Some participants indicated the application's Field of View (FOV) was insufficient (median 3). This might be motivated by the restricted view of the user's entire limbs through HoloLens, which could cause the user to switch between viewing their limbs and the app's panels. While using the program, most of the individuals did not report severe postural pain (median 3) or visual fatigue (median 3), although the findings show a larger variability for these items. Furthermore, some of them felt nausea, dizziness (median 5), or headaches (median 4). Although all participants used the MR application for the same amount of time and within the manufacturer's recommended usage limits, variability in the results can be explained by a number of factors, including differences in personal tolerance to pain and visual fatigue, individual adaptation to the application and the specific MR environment, and sensitivity to specific visual or sensory stimuli that may cause nausea, dizziness, or headaches. While some users may acquire more tolerance to the application stimuli with continuous usage, decreasing these effects, it is of utmost importance to assess each individual's eligibility for augmented therapy treatment. This justifies our decision to include a patient suitability assessment as part of the augmented therapy prescription process inside the proposed telemedicine framework, therefore ensuring safe and effective treatment for patients by putting their safety and well-being first.

The findings point to a positive overall experience in terms of engagement and user perception of their own performance during the activities. The majority of users felt they were able to complete the tasks satisfactorily (median 5). This is a significant indicator that users found the exercises manageable and that they were able to achieve their objectives effectively. The activities were believed to be engaging by users (median 5), indicating that they were actively involved and interested in the exercises, which can lead to a more enjoyable and effective user experience. Users reported no major sensations of irritation during the exercises (median 4) and did not believe they were required to put in much effort to accomplish their performance level. This shows that the exercises were not extremely difficult to perform and that users considered them comfortable. Low effort needs and the lack of frustration are essential for an optimal user experience, as frustration can detract from the overall efficacy of the MR solution.

Even though the usability evaluation of the MR solution was set up to reduce potential biases, there are still some risks that need to be taken into consideration for future investigations. Each participant in the current study was unfamiliar with XR technologies prior to testing, and each one followed the same protocol, conducting the evaluations in a controlled environment using the same device, ensuring consistency in terms of external conditions for all participants. Age-related biases, however, could still have an impact on the outcomes of these evaluations. Although it is crucial to consider users of different ages, given the broader audience our solution is aimed at, it is also necessary that, to ensure the generalizability of the framework, age-related factors, such as variations in cognitive processing speed or motor skills, will need to be further studied in future research, as they may impact user performance and usability perception. Another potential bias could arise from the propensity to use digital technologies. Despite all participants being selected to have no previous experience with XR, individual attitudes toward adopting new technologies may vary. To mitigate this, the framework already takes this factor into account by requiring participants to meet three key prerequisites (i.e., Patient's health condition, Patient's attitude in using digital technologies, Patient's willingness to undergo a digital therapy treatment) for accessing augmented therapy, ensuring that they possess the necessary familiarity and comfort with digital tools before starting treatment.

5.2 Hand gesture recognition evaluation

As can be seen in Fig. 8, training and validation loss, as well as training and validation accuracy, were plotted for each epoch using raw and interpolated values to show their trends. Both the validation metrics continue to improve for roughly 120 epochs, and then they remain unchanged or worsen, as can be inferred from both raw and interpolated values. As a result, the training was early stopped to prevent overfitting, and the best model, which corresponds

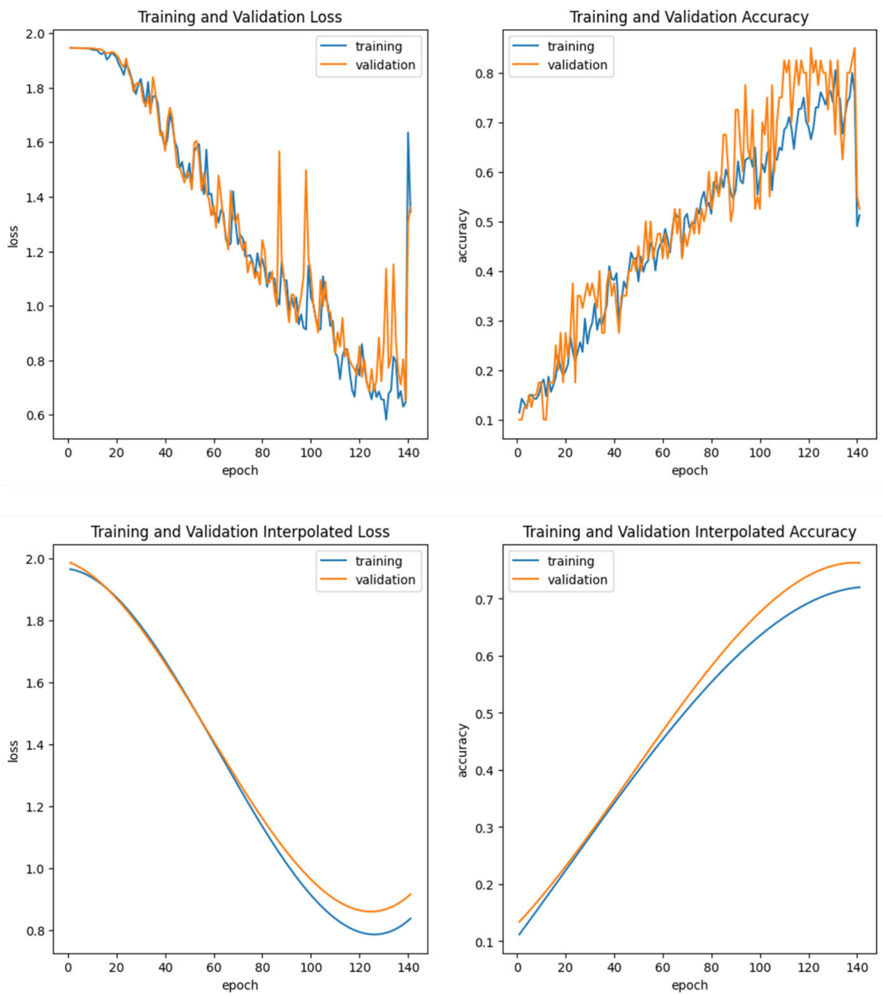


Fig. 8 Training and validation metrics trends. Raw loss and accuracy values were displayed in the upper part, while interpolated values are shown in the below part

to epoch 121, was selected for the final application. Specifically, validation accuracy was checked to terminate the learning phase prematurely. A 20-epoch threshold was defined to allow for no gain in accuracy. When the threshold was exceeded, training was stopped.

Both offline and live videos were used to evaluate the implemented LSTM network. Regarding offline tests, the LSTM model was assessed on the test set, and the results are displayed in Fig. 9 and Table 3. For model evaluation, 10-fold cross-validation was involved during training to obtain more representative and robust results. Specifically, the dataset was randomly split into 10 equal subsets. The model was trained on 9 subsets and tested on the remaining 1. This process is repeated 10 times, using a different subset for testing. As can be observed from the confusion matrix shown in Fig. 9, almost all test samples were accurately classified, except four samples. A video from the neutral class was incorrectly identified as belonging to the "thumb to annular finger opposition" class and vice versa. Two samples of the "thumb to index finger opposition" class are misclassified as "thumb to middle finger opposition" and "thumb to pinky opposition". Table 3 provides evidence of this since all classification metrics achieve remarkable values, with all macro averaged values greater than 80%, but strongly affected by the "none" class.

Afterward, additional tests were carried out by analyzing the webcam video stream to measure the model's performance in real-time. A total of 112 movements were executed and each gesture was repeated 16 times in random order. Figure 10 illustrates a few instances of accurately anticipated motions during real-time tests, with the predicted gesture reported at the top of each image and the estimated keypoints overlapping on the detected hand. Outstanding results were achieved in this instance, as seen by the confusion matrix shown in Fig. 11 and the classification metrics outlined in Table 4.

Most of the movements were correctly classified, even under real-time testing. Only one sample was misclassified for the categories "thumb to middle finger opposition" and "flexion

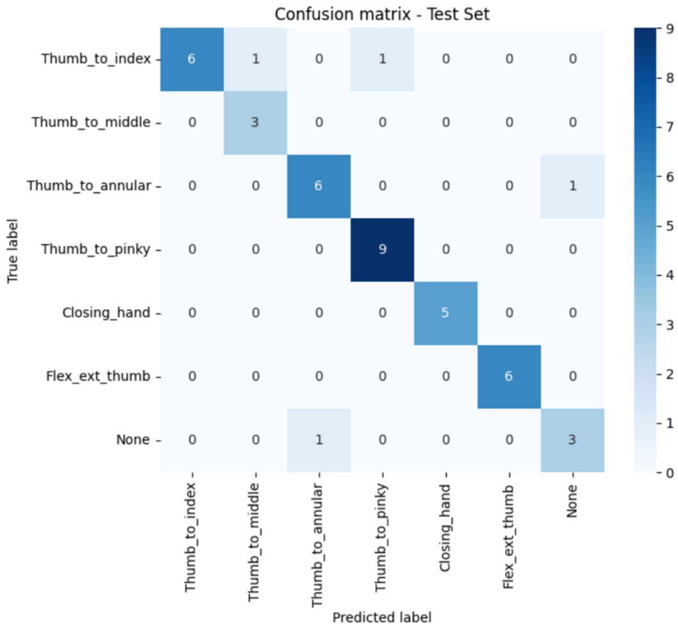


Fig. 9 Confusion matrix of test set videos

Table 3 Classification metrics on the test set videos

Class	Accuracy	Precision	Recall	F1-score
thumb to index	0.91 (0.80 - 1)	0.84 (0.72 - 0.96)	0.90 (0.80 - 1)	0.88 (0.77 - 0.95)
thumb to middle	0.89 (0.78 - 0.99)	**0.91 (0.83 - 0.98)**	0.89 (0.79 - 0.99)	0.89 (0.83 - 0.94)
thumb to annular	0.91 (0.81 - 1)	0.88 (0.74 - 1)	0.91 (0.81 - 1)	0.88 (0.77 - 0.99)
thumb to pinky	0.89 (0.79 - 0.98)	0.86 (0.70 - 1)	0.89 (0.79 - 0.98)	0.84 (0.75 - 0.95)
closing hand	**0.98 (0.94 - 1)**	0.90 (0.83 - 0.98)	**0.98 (0.95 - 1)**	**0.94 (0.89 - 0.99)**
flex ext thumb	0.84 (0.72 - 0.96)	0.75 (0.62 - 0.89)	0.84 (0.72 - 0.96)	0.77 (0.68 - 0.87)
none	*0.43 (0.23 - 0.63)*	*0.54 (0.29 - 0.79)*	*0.43 (0.23 - 0.63)*	*0.47 (0.26 - 0.67)*
macro avg	0.84	0.80	0.83	0.81

All the metrics were calculated separately for each class and then macro-averaged. The values are shown with related confidence intervals. The best-performing category for each metric is highlighted in bold and the worst in italics

and extension of the thumb.” The sample was assigned to the class “thumb to ring finger opposition” for the former class because the network misidentified the middle finger for the ring finger. Similarly, a sample from the “flexion and extension of the thumb” class was categorized as a “thumb to pinky opposition” gesture since the thumb movement is typically the same in both exercises and the network probably missed the pinky movement. In a comparable manner, two samples from the “thumb to pinky opposition” class were categorized as “thumb flexion and extension”. Instead, for the neutral class, five data were wrongly categorized, presumably because each exercise begins with the hand in a resting posture, which the network erroneously assumed was a movement. This generally affected the “flexion and extension of the thumb” and the “thumb to pinky opposition” exercises, suggesting that it might be challenging for the network to distinguish small finger movements

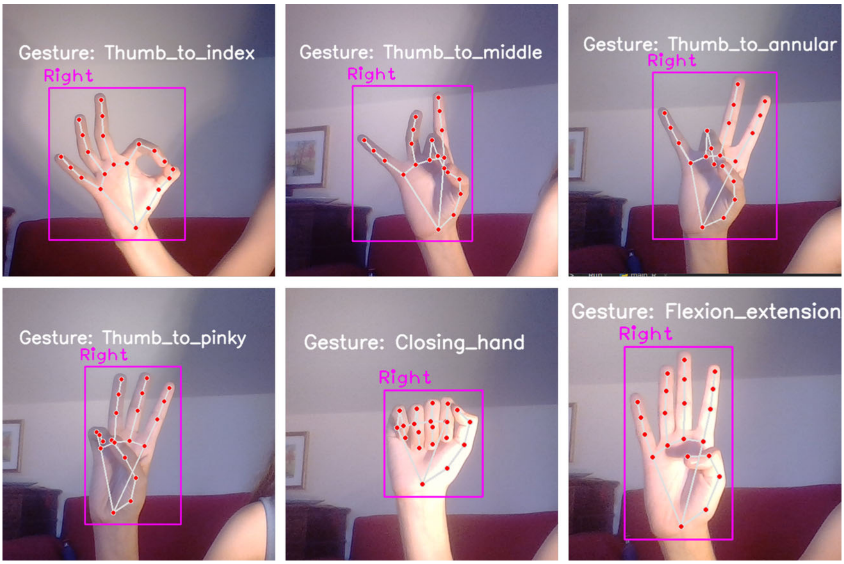


Fig. 10 Examples of exact detection of exercises achieved through tests conducted in real-time

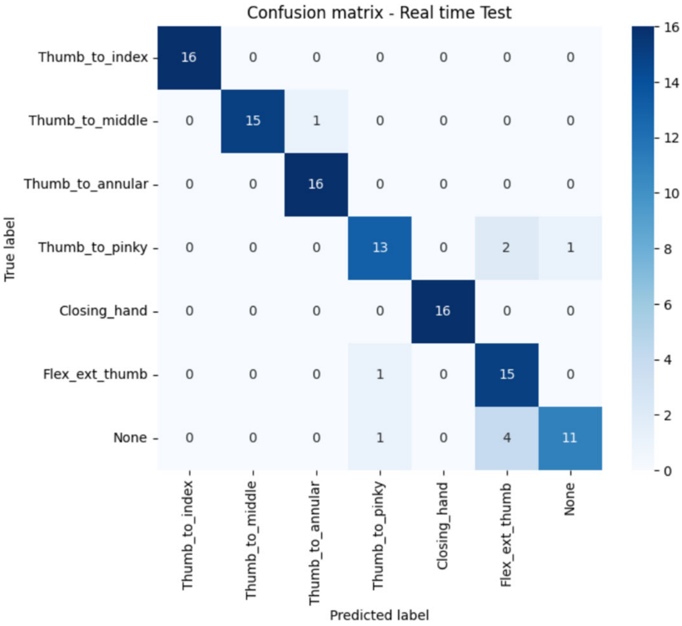


Fig. 11 Confusion matrix of real-time videos

and gestures made by the thumb when it is the only finger moving. Notwithstanding the slight difficulties of the real-time task, the network produced impressive outcomes, averaging a 91% accuracy and F1-score throughout all classes.

Statistical tests were conducted to determine whether a statistically significant difference existed between model performance on real-time tests and performance assessed on recorded video for all classes of gestures. The paired t-test was performed for each of the classification metrics considering both testing conditions, obtaining the following: accuracy p-value = 0.182, precision p-value = 0.056, recall p-value = 0.182, F1-score p-value = 0.108. Since a p-value greater than 0.05 was obtained for all metrics, no statistically significant differences can be determined between the performance of the model in real-time and on prerecorded video tests. These results imply that the model performs similarly in both testing conditions,

Table 4 Classification metrics on the real-time test

Class	Accuracy	Precision	Recall	F1-score
thumb to index	1.00	1.00	1.00	1.00
thumb to middle	0.94	1.00	0.94	0.97
thumb to annular	1.00	0.94	1.00	0.97
thumb to pinky	0.81	0.87	0.81	0.84
closing hand	1.00	1.00	1.00	1.00
flex ext thumb	0.94	0.71	0.94	0.81
none	0.69	0.92	0.69	0.79
macro avg	0.91	0.92	0.91	0.91

suggesting that its robustness can make it effective in real-life scenarios without losing reliability.

5.3 Ethical considerations

The proposed framework for home-based treatment of phantom limb pain through virtual mirror therapy presents some ethical and logistical challenges that must be highlighted for successful implementation.

From an ethical perspective, data privacy is a critical concern, as the system collects and processes sensitive patient information, including motion data and therapy progress metrics. Ensuring secure data storage, encrypted transmission, and strict compliance with privacy regulations like GDPR or HIPAA is essential to safeguard patient confidentiality and build trust.

Economic accessibility also poses a significant challenge, as the cost of Mixed Reality (MR) Head-Mounted Displays (HMDs) and associated technologies could limit access for underserved populations. For this reason, according to the proposed framework, the therapy center is intended to provide digital tools to the patients for the whole digital therapy duration. In this scenario, the economic impact is mitigated since hardware cost is not critical for health facilities.

Logistically, the adoption of such an advanced framework requires extensive training for healthcare professionals to operate MR systems and interpret Deep Learning (DL)-generated feedback effectively. This training introduces additional complexity and may encounter resistance in traditional healthcare settings. Nonetheless, this resistance can be mitigated by designing adaptable interfaces, useful both for physicians and patients. In this sense, the proposed case study was tested first on non-experts, to understand how to minimize the impact of the technology on the ultimate purpose of the application.

Modernizing healthcare infrastructure is another hurdle, as reliable internet access is necessary to support the framework's real-time MR functionalities, which may be unavailable in rural or remote areas. For this reason, HMD should incorporate local data storage and delayed synchronization. This method allows the therapy system to operate independently of real-time internet access while ensuring data integrity and eventual synchronization with healthcare providers once the network becomes available.

Ensuring integration with existing healthcare practices also requires developing protocols that bridge traditional in-person care and digital therapies seamlessly. In this perspective, future work on clinical validation could pave the way for the adoption of the proposed framework for different clinical conditions.

6 Conclusions

The integration of MR and Deep Learning technologies into the assessment of patients' MT exercises for home-based PLP treatment holds significant promise and potential benefits. The synergy between MR, which provides an immersive and interactive environment, and DL, which facilitates intelligent data analysis, creates a comprehensive solution for advancing the field of rehabilitation medicine.

The visual and interactive nature of MR technologies allows for a more accurate and personalized assessment of patients' MT exercises, capturing nuanced movements and providing valuable insights into their progress. On the other hand, the incorporation of DL algorithms allows for the analysis of vast amounts of data generated during MT sessions, identifying subtle patterns and trends that may elude traditional assessment methods. The intelligent analysis enables healthcare professionals to tailor treatment plans more precisely, adapting to individual patient needs and optimizing therapeutic outcomes.

Future research will be focused on the clinical validation of the proposed framework to optimize the support that the explored digital technologies can provide to healthcare operators, safeguarding patient welfare and maintaining the highest standards of care. Evaluations will be conducted in clinical settings with a significantly larger sample of patients suffering from phantom limb pain (PLP), to ensure that the findings are not only scientifically valid but also directly applicable to real-world clinical practice. This expanded patient cohort will enable us to gather more comprehensive data, allowing for a deeper understanding of the efficacy and practicality of our approach in a clinical context. By testing in environments that closely mirror actual clinical conditions, we aim to confirm the generalizability and robustness of the results, thereby enhancing the potential for real-world implementation and ultimately improving patient outcomes. The study will include two groups of pathological subjects: one group undergoing traditional mirror therapy and the other group participating in the augmented therapy outlined in our framework. By incorporating both approaches, we aim to conduct a comprehensive and rigorous comparison between the conventional therapy and the innovative augmented approach. This comparative study design will allow us to thoroughly assess the effectiveness of the augmented therapy, not only in terms of its clinical outcomes but also in its potential to offer enhanced benefits over the traditional method. Such a comparison is crucial for determining whether the augmented therapy can provide superior rehabilitation outcomes, and ultimately, whether it can be considered a viable alternative or complement to existing techniques in clinical practice. Moreover, long-term assessments will be integrated as part of the upcoming clinical evaluations to determine whether the therapy's benefits are sustained over time, in addition to addressing short-term efficacy. This multifaceted strategy will ensure that the proposed structure contributes to long-term patient outcomes as well as immediately meeting therapeutic needs.

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Availability of Data and Materials Upon request

Declarations

Conflict of Interest/Competing Interests The authors have no competing interests to declare that are relevant to the content of this article.

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