Self-Similarity Beats Motor Control in Augmented Reality Body Weight Perception

Marie Luisa Fiedler, Mario Botsch, Carolin Wienrich, and Marc Erich Latoschik

Fig. 1: The figure shows all experimental conditions from an observer's perspective over the participant's shoulder, arranged left to right as follows: (1) self-similar controlled virtual human, (2) generic controlled virtual human, (3) self-similar non-controlled virtual human, (4) generic non-controlled virtual human.

Abstract—This paper investigates if and how self-similarity and having motor control impact sense of embodiment, self-identification, and body weight perception in Augmented Reality (AR). We conducted a 2x2 mixed design experiment involving 60 participants who interacted with either synchronously moving virtual humans or independently moving ones, each with self-similar or generic appearances, across two consecutive AR sessions. Participants evaluated their sense of embodiment, self-identification, and body weight perception of the virtual human. Our results show that self-similarity significantly enhanced sense of embodiment, self-identification, and the accuracy of body weight estimates with the virtual human. However, the effects of having motor control over the virtual human movements were notably weaker in these measures than in similar VR studies. Further analysis indicated that not only the virtual human itself but also the participants' body weight, self-esteem, and body shape concerns predict body weight estimates across all conditions. Our work advances the understanding of virtual human body weight perception in AR systems, emphasizing the importance of factors such as coherence with the real-world environment.

Index Terms—Virtual human, augmented reality, self-similarity, motor control, body weight perception, body image, sense of embodiment, self-identification, coherence

1 Introduction

Body image disorders represent a significant global public health challenge, impacting individuals across demographics and leading to severe physical, psychological, and social consequences [43]. Despite current therapies, rising prevalence and relapse rates emphasize the demand for innovative treatments. Virtual Reality (VR) technology has emerged as a promising tool with the potential to revolutionize body image disorder interventions [21, 31, 53]. A key feature of VR is immersing affected people in a virtual body and modifying their virtual body weight [9, 21, 23, 28, 41]. Within this context, two factors emerge as pivotal factors shaping perceptions of virtual bodies: self-similarity in the appearance between the virtual human and the user and having motor control over the virtual human's body movements through visuomotor synchrony in the movements between the virtual human and the user [13, 26, 32, 38, 51, 52, 64]. Consequently, virtual humans can be valuable tools in revealing existing body misperceptions or cultivating a realistic image of one's current and desired body shape [9, 23, 28, 41]. While virtual humans in VR can be powerful tools for addressing body misperceptions, Augmented Reality (AR) offers distinct advantages in medical settings. Notably, AR allows patients to stay within familiar environments and maintain direct interaction with therapists, which is crucial for building a therapeutic alliance [11, 15, 16]. Integrating AR into daily life can enhance treatment acceptability by minimizing patient routine disruptions and fostering alliance formation. However, while body weight perception of virtual humans has been widely studied in fully immersive VR systems [14, 32, 37, 53, 61, 64], research using AR systems is just beginning [34, 61, 62]. Furthermore, AR's altered immersion level may impact body weight perception of virtual humans, raising questions of whether AR and VR similarly influence virtual human body perception and whether the same factors influence them.

With this work, we extend prior VR research by investigating the visual perception of virtual humans in AR. Using state-of-the-art photogrammetry techniques, we generated photorealistic virtual humans in a controlled user study with 60 participants. In a 2×2 mixed design, we (1) applied self-similar or generic textures to the virtual human and (2) gave the participants either motor control over the virtual human's body movements (controlled virtual human) or had it move indepen-

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dently of the participant (non-controlled virtual human). Participants performed body movement and weight estimation tasks while observing the virtual human. After each AR exposure, participants answered questions about their perceived sense of embodiment (SoE) and self-identification. We further considered the influence of participants' body weight, self-esteem, and body shape concerns on their body weight estimations. Furthermore, we conducted semi-structured interviews after each condition to better understand the participants' experiences. Overall, our study explores how VR research on virtual human design can be applied to AR. We aim to enhance the understanding of virtual humans' body weight perception in AR systems and investigate whether AR's proposed advantages can be effectively harnessed or if they come with limitations that affect body weight perception. Our work underscores the importance of self-similarity in appearance over having motor control over the virtual human body movements in shaping perception while noting that the effects of having motor control are less pronounced compared to VR systems.

2 Related Work

2.1 Perception of Virtual Humans in VR

Previous VR research revealed two factors that influence how users perceive virtual humans: (1) self-similarity in appearance, where virtual humans are self-similar in their texture and body shape to match the user visually [32, 38, 51, 52], and (2) having motor control over the virtual human's movements through visuomotor synchrony in the movements between the virtual human and the user, allowing the virtual human to act as the user's virtual body [61, 64]. Previous work showed that both factors enhance SoE and self-identification with virtual humans in VR [13, 47, 52, 55, 64]. As Kilteni et al. [26] defined, SoE characterizes the subjective reaction and quality of having this body as the sense of owning, controlling, and being inside a virtual body, commonly known as virtual body ownership, agency, and self-location [26]. Self-identification, in contrast, can be described as the "process of identifying a representation as being oneself" [18, p.1]. Fiedler et al. [13] divided self-identification into perceived self-similarity between the user and the virtual human, and self-attribution of personal characteristics, both external body features and internal character traits, to the virtual human.

Previous research suggests that having motor control over a virtual human's movements and self-similarity in its appearance influence the user's body perception of virtual humans. Users estimated the body weight of photorealistic self-similar virtual humans more accurately than that of generic ones with checkerboard [38, 52] or antropomorphic [14] textures. Thaler et al. [51] found an influence of the user's body weight on body weight estimation accuracy, but only with self-similar virtual humans, suggesting self-identification as a potential influencing factor. Self-similar virtual humans resembling the user's own identity more closely could lead to a more accurate estimation of body weight. Mölbert et al. [32] reported contrasting findings, suggesting increased misestimation when the virtual human resembled the user more closely. Regarding motor control, Wolf et al. [61] observed similar effects on body weight estimation for generic controlled virtual humans as Thaler et al. [51] did for self-similar ones. In a later work, Wolf et al. [64] showed that users' body weight influenced estimations only when estimating controlled virtual humans, not non-controlled ones. Furthermore, users underestimated the body weight of controlled virtual humans significantly compared to estimating non-controlled ones [14, 64]. Neyret et al. [33] found that observing one's own body as a non-controlled virtual human improved body shape evaluation among females, fostering a more positive self-perception. Prior research suggests self-esteem and body shape concerns influence real body perception [24, 36]. Similarly, these factors may also affect the body perception of virtual humans [14, 60]. However, Thaler et al. [51] found no impact.

2.2 Perception of Virtual Humans in AR

While the perception of virtual humans in VR is well-researched, Weidner et al. [57] identified only six papers in their meta-analysis that evaluated virtual humans in AR. They concluded that while AR and VR experiments yield similar results, none of the analyzed studies directly compare them. The researchers assert that their high-level findings may apply interchangeably between AR and VR. The review of Genay et al. [16] gathered knowledge on SoE of virtual humans in AR. They extended VR research and concluded that in AR, the ability of users to develop SoE towards virtual body parts [44, 45, 50, 66] and entire virtual bodies [34, 61, 62] is also possible.

Body weight perception of virtual humans was examined explicitly in only four studies in AR [34, 61–63]. In the study of Nimcharoen et al. [34], the users estimated the body weight of 3D point cloud body representations of themselves in an optical see-through AR system. The authors reported that body weight perception was similar between their system and a comparable VR system by Piryankova et al. [38]. The studies by Wolf et al. [61–63] compared body weight perception between VR, video see-through AR, and optical see-through AR systems for generic controlled virtual humans [61, 62] and self-similar non-controlled virtual humans [63]. They found that different display types can highly distort body weight perception, underscoring the substantial impact of the system on the user's perception. This finding suggests the need to systematically replicate VR research findings in AR contexts to test their transferability. Furthermore, no research exists on how personal body weight, self-esteem, and body shape concerns influence body weight perception in AR.

2.3 Why Does Perception of Virtual Humans Differ in AR and VR?

While the studies mentioned provide empirical results, current theory-based work indicates why the perception of virtual humans and its influencing factors could differ between AR and VR.

Skarbez et al. [48] revised Milgram's reality-virtuality continuum as a taxonomy for mixed, augmented, and virtual reality (summed up as eXtended Realities, XR for short) experiences, outlining three dimensions: (1) immersion, which is determined by hardware specifications, (2) extent of world knowledge, which describes the degree of reality a system incorporates, and (3) coherence, which refers to sensory information conformity. Transitioning from VR to AR affects all three dimensions. AR systems possess lower immersion but a greater extent of world knowledge due to real-world inclusion. For coherence, Skarbez et al. [48] highlight that in VR, coherence is primarily internal, meaning that it is essential that virtual objects interact predictably with each other and the user. In AR, coherence shifts to external factors, assessing how virtual objects interact predictably with real objects and the user. Similarly, Wienrich et al. [59] propose various frames of reference in VR and AR that users can use to orient themselves and evaluate the coherence of their experience.

Latoschik and Wienrich [27] propose an alternative theoretical model centering around congruence and plausibility. They define congruence as the objective match between processed and expected information, while plausibility is the subjective evaluation of this congruence. They argue that all congruence activations contribute to the plausibility of an XR experience. Unlike in VR or the real world, where the visual impression of the objects and the environment either is congruent by nature or can be rendered in a congruent fashion, current AR systems exhibit a visual difference between real and rendered objects due to various technical differences between the way rendered objects are synthesized and then composed with the reproduction of the real objects. [17]. Therefore, these incongruencies of AR systems may potentially influence the perception of virtual humans, virtual agents, and the users' own avatars embedded as computer-generated content in the physical environments captured by the AR display. Fittingly, Wolf et al. [63] investigated the plausibility of virtual humans in AR and VR systems. While they found no significant differences in the virtual human's appearance and behavior between systems, they showed that incongruence between viewing a rendered human in a real AR environment and a rendered VR environment had a significant effect.

2.4 Summary

The key advantage of AR over VR systems is their ability to keep users in the real world and connected to their therapist during exposure.

However, this integration of real and virtual elements may influence the perception of the virtual human, potentially leading to a less coherent experience [27, 48, 59]. Comparative studies [62, 63] confirm previous assumptions that the respective system has an effect [16, 57], complicating the direct transfer of findings from VR to AR systems. To our knowledge, no study has systematically investigated the impact of controlling the virtual human's movements and its self-similarity in the appearance on virtual human body weight perception in AR. Thus, we aim to fill this gap and assess the transferability of current VR research findings of virtual human body weight perception to AR.

We expect that manipulating these factors impacts the perceived SoE as described in Sec. 2.2. Due to limited AR research, we explore their impact on self-identification based on current VR research derived from the literature described in Sec. 2.1, leading to the following hypotheses:

H1.1: Controlled virtual humans are rated higher in sense of embodiment than non-controlled ones.

H1.2: Self-similar virtual humans are rated higher in sense of embodiment than generic ones.

H1.3: Controlled virtual humans are rated higher in self-identification than non-controlled ones.

H1.4: Self-similar virtual humans are rated higher in self-identification than generic ones.

Again, due to limited AR research available, we explore the factors' impact on virtual human body estimation in AR systems based on current VR research derived from the literature described in Sec. 2.1 with the following hypotheses:

H2.1: The body weight of controlled virtual humans is estimated less accurately than that of non-controlled ones.

H2.2: The body weight of self-similar virtual humans is estimated with a different accuracy than that of generic ones.

H2.3: Body weight estimations of controlled virtual humans or self-similar virtual humans are influenced by participants' body weight.

3 METHOD

3.1 Participants

Our study complied with the ethical guidelines outlined in the Declaration of Helsinki and received approval from the local Ethics Committee at the University of Würzburg. We enrolled 60 participants through the local participant management system. 17 were undergraduates who earned course credits. The remaining 43 participants received monetary compensation. All participants fulfilled the criteria: (1) regular or corrected vision and hearing, (2) a minimum of ten years of German language proficiency, (3) no diagnosed eating-related and body weight-related diseases, and (4) no reported sensitivity to simulator sickness. We excluded one participant due to technical problems. The final pool comprised 59 participants (41 female, 18 male) aged 19 to 49 ($M = 26.58$, $SD = 6.53$) years and the following ethnic distribution: 54 Caucasian, 2 MENA, 1 AIAN, 1 Asian, 1 Hispanic. Detailed demographic data and group comparisons are provided in Table 2.

3.2 Design

Our study utilized a 2×2 mixed design incorporating two independent variables: having motor control over the virtual human (short: motor control) as a between-subject factor and self-similarity in the appearance (short: self-similarity) as a within-subject factor. We opted for a mixed design primarily due to time and cost constraints. We implemented the motor control factor as a between-subject factor because there is limited evidence on how long a perceived SoE toward a virtual human can be sustained. To avoid potential carryover effects in the motor control condition, we chose self-similarity as the within-subject factor and motor control as the between-subject factor.

We randomly assigned participants to either the control condition, where they interacted with a movement-controlled virtual human achieved through visuomotor coupling of the participant's movements and the virtual human, or the non-control condition, where they interacted with a virtual human moving independently of the participant. In both conditions, the virtual human was presented in a scenario matched to the (non-) coupled movements. The participant observed the controlled virtual human through a virtual mirror, while they observed the non-controlled virtual human through a door frame in an adjacent room. In both conditions, participants experienced a self-similar virtual human in the self-similarity condition and a gender-matched generic virtual human in the non-self-similarity condition. We illustrated all conditions in Fig. 1. The allocation of conditions was counterbalanced to minimize bias. As dependent variables, we measured participants' perceived SoE, self-identification, and perception of the virtual human's body weight. We included the personal body mass index (BMI), signs of simulator sickness, perceived eeriness of the virtual human, body shape concerns, and self-esteem as control variables.

3.3 System Description

3.3.1 AR System

We developed the AR system using Unity 2021.3.32f1 LTS, integrating the hardware using the Oculus XR plugin version 3.3.0. The system ran on a Windows 10 workstation (Intel Core i7-9700K, NVIDIA GeForce RTX 2080 SUPER, 16 GB RAM). We used a Meta Quest Pro[1] video see-through AR head-mounted display (HMD) with a resolution of $1800\,px \times 1920\,px$ per eye, a total field of view of $106° \times 96°$, and a refresh rate of 90 Hz. We measured the system's motion-to-photon latency by counting frames between real and rendered movements [49]. Using an iPhone 13 high-speed camera, we recorded the user's motions and the corresponding virtual human's reactions through the see-through display at 240 fps. The average motion-to-photon latency for the whole body pose was 71.75 ms, which we considered sufficiently low [56].

Our AR system displayed virtual objects on the wall facing the participant, varying by the motor control condition. In control conditions, we augmented a virtual full-body mirror into the laboratory, showing the participant's controlled virtual human from an allocentric perspective (see Fig. 1, first and second picture). The mirror stood 2 m away, setting a total observation distance of 4 m between the participant and the controlled virtual human. We also created a 3D model of the laboratory for a realistic background in the virtual mirror. Test instructions were presented on a virtual board to the mirror's right. In non-control conditions, we augmented the laboratory with a virtual door frame leading to an adjacent, differently furnished virtual room, maintaining the same dimensions as the real room (see Fig. 1, third and fourth picture). The non-controlled virtual human was placed 4 m from the participant, visible through the door frame, offering a view similar to the control conditions. Instructions were displayed on a virtual board to the right of the door frame. In all conditions, participants could view their real surroundings and own body from an egocentric perspective.

3.3.2 Virtual Human Generation

We used a custom-made photogrammetry rig and pipeline to scan participants. First, we captured the photos of the participant by a setup including 15 DSLR cameras mounted on a rig in a 5×3 matrix (2.04 m width; 3.32 m height) and a workstation (Intel Core i9-9900KF, NVIDIA RTX 2080 Ti, 32 GB RAM, Ubuntu 20.04.6 LTS). The camera matrix comprises three horizontal bars spaced 1 m apart, with five cameras mounted on each bar. All cameras are aligned to capture the participant's entire body, who stands 2 m from the scanner. To generate photorealistic virtual humans, we employed the method of Achenbach et al. [1], which involves fitting an animatable body model to a dense point cloud and optimizing alignment, pose, and shape through non-rigid ICP and surface deformation. We scanned the participants from four sides of their body: front, back, left, and right, resulting in four point clouds. We selected multiple landmarks per scan to establish initial correspondences with the model, optimizing pose and shape

[1] https://www.meta.com/quest/quest-pro/

parameters to align with all point clouds. Finally, texture information was created following the method of Wenninger et al. [58], synthesizing and merging partial textures from camera calibration data using graph-cut optimization and Poisson Image Editing. A detailed description of the process can be found in the work of Mal et al. [29].

The resulting self-similar 3D model and photorealistic texture can be directly imported into Unity using a custom FBX-based runtime importer. We added no post-processing to the created virtual humans. To create the generic-looking virtual humans, we adopted a method from previous studies [38, 51] without any amendments by taking the body shape of the self-similar 3D model and replacing the texture with a gender-specific, generic texture corresponding to the typical appearance of the local population.

3.3.3 Virtual Human Animation

In the control conditions, we employed Captury's markerless tracking system[2] for body tracking. With eight FLIR Blackfly S BFS-PGE-16S2C RGB cameras mounted on the laboratory ceiling, the system tracks the participant's body movements at a rate of 70 Hz. The cameras were connected to a workstation (Intel Core i9-11900K, NVIDIA GeForce RTX 3090, 64 GB RAM, Ubuntu 22.04.1 LTS) running Captury Live version 261b. The body movements were streamed continuously to the AR system via a 1 GBit/s ethernet connection and integrated using Captury's Unity plugin. Then, we retargeted the received body pose to the corresponding controlled virtual human, merging it with the remaining tracking data from the AR system through Unity's avatar animation system and a custom-written retargeting script. We synchronized the virtual human's hand movements with those captured by the controllers to enhance stability and accuracy in the hand poses.

In the non-control conditions, the non-controlled virtual human was animated using pre-recorded animation sequences captured using the Xsens motion capture system suit with the MVN Link system [30]. As with the controlled virtual human, the hands and facial expressions were shown in a neutral, non-animated pose.

3.3.4 Virtual Human Body Weight Modification

We implemented a statistical model for realistic modification of virtual humans' body weight, adopted without any amendments from prior work [10]. This model, based on anthropometric data from the European CAESAR database [42], allows dynamic body weight adjustments for males and females during runtime, ensuring realistic changes in body shape while preserving facial proportions and details. For one experimental task, participants had to interactively change the virtual human's body weight. We Without any amendments, adopted a gesture-based interaction method from Döllinger et al. [10], where participants adjusted body weight by pressing the trigger buttons on controllers and moving them closer together or farther apart. The rate of change depended on the speed and distance of the movement. The range of body weight adjustment was limited to $\pm 35\,\%$ of the participants' actual body weight to maintain realistic and comfortable body shapes.

3.4 Measures

3.4.1 Quantitative Questionnaires

Participants completed questionnaires using LimeSurvey 4 and verbally answered in-experience questions. The questionnaires used are listed in Table 1. We ensured questionnaire accuracy by using validated translations or conducting back-and-forth translations for questions in German language. We used the Virtual Embodiment Questionnaire (VEQ) [46] to measure SoE, as we also aimed to capture self-identification with the virtual human. To this end, we found that Fiedler et al. [13] introduced a set of items for measuring self-identification, often used alongside the VEQ. This combination primarily motivated our choice of the VEQ.

3.4.2 Body Weight Perception

We utilized two tasks described below to assess the participants' body weight perception. Therefore, we measured the BMI, which is calculated as $\text{BMI} = \frac{\text{body weight in kg}}{(\text{body height in m})^2}$.

[2]https://captury.com/resources/

Table 1: Overview of the questionnaires used during the study. * marks the questionnaire used as a manipulation check for the motor control factor, † marks the one for the self-similarity factor.

Questionnaire	Measure	Range
Sense of Embodiment		
VEQ [46]	Virtual Body Ownership	[1–7]
	Agency*	[1–7]
VEQ+ [13]	Self-Location	[1–7]
Self-Identification		
VEQ+ [13]	Self-Attribution	[1–7]
	Perceived Self-Similarity†	
Controls		
SSQ [2]	Simulator Sickness	[0–235.62]
UVI [20]	Eerieness	[1–7]
RSES [12]	Self-Esteem	[0–30]
BSQ [40]	Body Shape Concerns	[34-204]

Passive Estimation Task (PET) We adopted the task from previous work [10, 63] without any amendments to investigate the participant's perception of virtual human body weight by numerically estimating it. Over nine trials, we adjusted the virtual human's body weight in 5 % intervals within a range of $\pm 20\,\%$. Participants verbally estimated body weight in kilograms. We blacked out the HMD during the modifications to avoid any hints. To attain a holistic perspective, as suggested by prior work [7], participants were either instructed to move and turn in front of the virtual mirror or to observe the non-controlled virtual human doing it independently.

To measure estimation accuracy, we calculated the relative misestimation (M) using the formula $M = \frac{e-p}{p}$, where e is the estimated weight and p is the presented virtual human's body weight. A negative value indicates underestimation and a positive value indicates overestimation. Out of this, we computed the average misestimation over all nine estimations (PET $\overline{M} = \frac{1}{9}\sum_{k=1}^{9} M_k$) and the absolute average misestimation (PET $\overline{A} = \frac{1}{9}\sum_{k=1}^{9} |M_k|$) to assess general estimation ability and accuracy across conditions, respectively. PET $\overline{M}$ measures the participant's ability to estimate the virtual human's absolute body weight. PET $\overline{A}$ quantifies the magnitude of individual estimations, reflecting the absolute accuracy of estimations across different conditions.

Active Modification Task (AMT) We modified a task from previous work [10, 33, 51] to explore participants' perceptions of virtual human body weight and their own body image. This task required adjusting the virtual human's body weight to match the participant's current and ideal body weights. Before each estimation, we randomly set the virtual human's body weight within $\pm 10\,\%$ of the participant's actual body weight while the HMD was blacked out. As for the PET, participants were asked to turn in front of the virtual mirror or observe the non-controlled virtual human.

We calculated the relative misestimation of the participant's real body weight by using the formula $M = \frac{m-r}{r}$, where m represented the virtual human's modified body weight to the participant's estimated current (AMT current) or ideal (AMT ideal) body weight and r the participant's real body weight. Negative values indicated underestimation, while positive values indicated overestimation compared to r.

3.4.3 Qualitative Interview

We conducted semi-structured interviews post-exposure to gather feedback on how participants perceived the exposure and the presented virtual human with the following questions: (1) "How did you experience the exposure scenario?"; (2) "How did you experience the interaction with the virtual human?"

3.5 Procedure

Our study followed a standardized procedure, detailed in Fig. 2, with an average duration of 80 min and each AR session lasting about 12 min. Initially, participants created two personal pseudonymization codes for data storage and provided consent. We instructed them to wear tight-fitting, non-monochromatic clothing, remove any accessories, and measured their body height and body weight without shoes before the scan. The entire scan, from photo capture to virtual human generation, took approximately 25 min.

Before each AR exposure, participants were instructed on using the HMD and controllers, then entered a preparation environment that augmented the real laboratory with a virtual board for eye tests and virtual human calibration. Subsequently, we blacked out the HMD, and participants saw a virtual mirror or door frame, depending on the motor control factor, and initiated a pre-programmed test sequence with instructions from pre-recorded voice commands and the virtual board.

After orienting themselves, participants performed five body movement tasks, adopted without any amendments from previous work [61], each lasting 20 sec, designed to induce SoE by the virtual human mirroring the participant's movements to promote visuomotor coupling in the control conditions. In the non-control conditions, the non-controlled virtual human performed the tasks out of sync with the participant to avoid visuomotor coupling. Following this, PET and AMT tasks were conducted as described in Sec. 3.4.2. After each AR exposure, participants were interviewed and completed post-experience questionnaires. The process was repeated for the second AR exposure and concluded with the final post-questionnaire before compensation was provided.

4 Results

We used R version 2022.07.2[3] for statistical analysis and examined group homogeneity using non-parametric Mann-Whitney-U tests due to data violating normal distribution assumptions. The results are summarized in Tab. 2. We did not observe significant systematic simulator sickness in SSQ pre- and post-scores ($V(59,59) = 2386, p = .336$). While two participants exceeded the simulator sickness threshold of 20 points [2], with the highest increase noted at 41.14 points, none reported experiencing simulator sickness symptoms during exposure. Consequently, we retained these participants in the data analysis.

4.1 Manipulation Check

We calculated 2×2 mixed ANOVAs for each variable of SoE, self-identification, and the control measure eerieness. As a manipulation check for our factors, we used agency (VEQ) to assess the motor control factor and perceived self-similarity (VEQ+) to evaluate the self-similarity factor. For variables not meeting normality or homoscedasticity assumptions, we compared results with non-parametric analyses of longitudinal data [4] from the R package nparLD [35] and found no difference. Therefore, we reported the results of the parametric tests for all variables. We performed all tests against an α of .05. All descriptive values are shown in Tab. 3. For clarity, we report only the significant results below, while non-significant test results are added to the supplementary material.

[3]https://www.R-project.org/

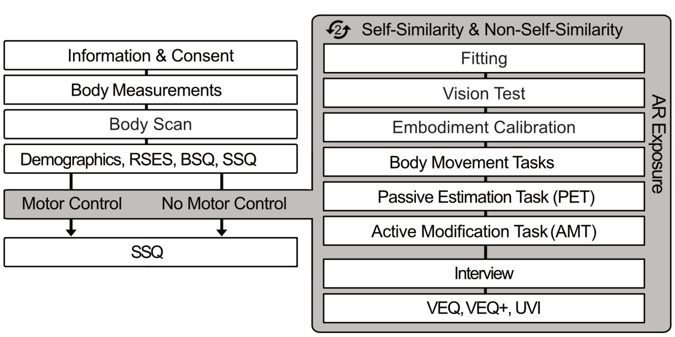

Fig. 2: The figure outlines the study procedure, detailing the AR exposure on the right. Participants underwent the exposure either in the control or non-control conditions, consecutively counterbalanced between self-similar and non-self-similar conditions.

Table 2: The table shows the descriptive values and pairwise comparisons of the control measures for the between factor motor control (MC /non-MC).

	MC	non-MC	
	M (*SD*)	*M* (*SD*)	Test statistics
Age	28.23 (8.20)	24.97 (4.05)	$U(30,29) = 501.0, p = .314$
BMI	22.86 (2.90)	23.18 (2.88)	$U(30,29) = 400.0, p = .596$
BSQ	63.89 (19.88)	72.40 (39.18)	$U(30,29) = 429.0, p = .927$
RSES	21.80 (3.40)	20.76 (3.57)	$U(30,29) = 501.0, p = .314$
Pre-SSQ	21.57 (23.99)	19.22 (18.87)	$U(30,29) = 428.5, p = .921$
Post-SSQ	21.57 (17.57)	12.64 (9.83)	$U(30,29) = 578.0, p = .029$
SSQ Diff.	0.00 (18.06)	-6.58 (15.18)	$U(30,29) = 554.5, p = .068$

4.1.1 Sense of Embodiment

As expected, our calculations revealed significantly higher scores for controlled virtual humans for agency ($F(1,57) = 153.634, p < .001, \eta_p^2 = 0.729$). However, we only found tendencies for virtual body ownership when the participants controlled the virtual human ($F(1,57) = 2.982, p = .090, \eta_p^2 = 0.050$) and no significant result for self-location. Further and as expected, we found significantly higher scores for self-similar virtual humans for virtual body ownership ($F(1,57) = 33.767, p < .001, \eta_p^2 = 0.372$), agency ($F(1,57) = 13.041, p < .001, \eta_p^2 = 0.186$), and self-location ($F(1,57) = 28.264, p < .001, \eta_p^2 = 0.331$). We found an interaction effect for the perceived agency ($F(1,57) = 7.368, p = .009, \eta_p^2 = 0.114$), but not for virtual body ownership and self-location. Post-hoc T-tests with Tukey correction revealed higher agency scores for self-similar controlled virtual humans as for self-similar non-controlled ones ($t(57) = 10.614, p < .001, d = 2.764$), for self-similar controlled virtual humans as for generic ones ($t(57) = 12.882, p < .001, d = 3.639$), for generic controlled virtual humans as for self-similar non-controlled ones ($t(57) = 10.392, p < .001, d = 3.222$), for generic controlled virtual humans as for generic non-controlled ones ($t(57) = 12.679, p < .001, d = 3.302$), and self-similar non-controlled virtual humans as for generic non-controlled ones ($t(57) = 4.435, p < .001, d = 0.508$). Overall, we partially confirmed hypothesis H1.1, fully confirmed H1.2, and validated our manipulation check for the motor control factor, with higher agency for controlled virtual humans than non-controlled ones.

4.1.2 Self-Identification

We found tendencies for a main effect of having motor control for self-attribution ($F(1,57) = 3.558, p = .064, \eta_p^2 = 0.459$) with higher scores for controlled virtual humans compared to non-controlled ones and no effect for perceived self-similarity. As expected, our calculations revealed a main effect for self-similarity with higher scores for self-similar virtual humans compared to generic ones for self-attribution ($F(1,57) = 44.836, p < .001, \eta_p^2 = 0.440$), and perceived self-similarity ($F(1,57) = 110.835, p < .001, \eta_p^2 = 0.660$). We found no interaction effect for self-attribution and perceived self-similarity. Overall, we did not confirm hypothesis H1.3 but confirmed H1.4 and validated the self-similarity manipulation, with higher perceived self-similarity for self-similar virtual humans than generic ones.

4.1.3 Eerieness

We found no influence of our factors on the perceived eerieness of the virtual human.

4.2 Body Weight Perception of Virtual Humans

We calculated $2 \times 2 \times 2$ mixed ANOVAs for each variable of PET and AMT. We compared the results with non-parametric analyses as in Sec. 4.1. If there was a difference in the significance of the results, we reported the result of the more conservative, non-parametric test. Next to the factors self-similarity and motor control, we included the participants' gender to control for gender-specific differences, as previous studies suggest an influence on body weight estimation [6, 22].

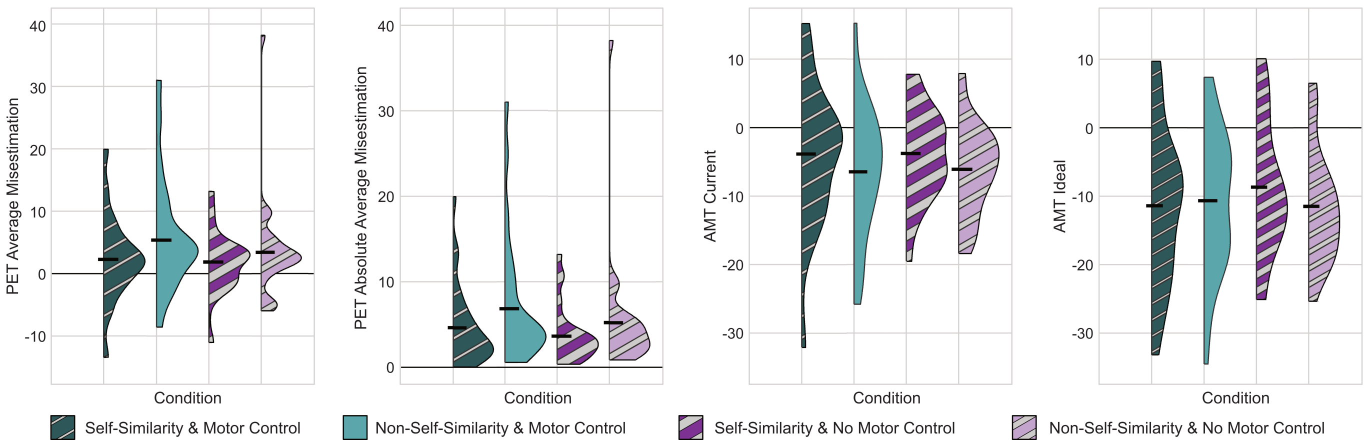

Fig. 3: The figure shows half violin plots for all descriptive mean values of the body weight perception task variables, shown on the y-axis. The condition factor is plotted on the x-axis.

We performed all tests against an α of .05. All descriptive values are shown in Tab. 3 and plotted in Fig. 3. Again, non-significant test results are in the supplementary material.

To better identify which facets of the participant influence body weight perception of virtual humans in AR, we calculated two kinds of multiple regressions for each body weight estimation variable of PET and AMT: (1) To explore the influence of the participant's body itself, we analyzed the relationship between the participant's BMI, its interaction with both factors and body weight perception variables. (2) To understand the impact of the participant's body image, we examined the relationship between their self-esteem, body shape concern, their interaction with both factors and body weight estimation variables. All calculated regressions are shown in Tab. 4.

4.2.1 Influence of Self-Similarity, Motor Control, and Gender

Passive Estimation Task (PET) For PET $\overline{M}$, we found a main effect of self-similarity with significantly more accurate estimations for self-similar virtual humans ($F(1,55) = 13.132, p = .001, \eta_p^2 = 0.193$). We found no effect of having motor control and no interaction effect. Moreover, male participants ($M = 6.04$, $SD = 7.74$) misestimated the virtual humans' body weight significantly more than females ($M = 2.01, SD = 6.20$) ($F(1,55) = 5.653, p = .021, \eta_p^2 = 0.093$). For PET $\overline{A}$, our calculations also revealed a main effect of self-similarity with more accurate estimations for self-similar virtual humans ($F(1,55) = 15.691, p < .001, \eta_p^2 = 0.222$). We also observed an interaction effect between self-similarity and gender ($F(1,55) = 10.573, p = .002, \eta_p^2 = 0.161$). Post-hoc T-tests with Tukey correction showed that male participants estimated the body weight of generic virtual humans ($M = 9.04$, $SD = 9.35$) less accurately than female participants estimated the body weight of self-similar ones ($M = 4.22$, $SD = 4.24$) ($t(57) = 2.845, p = .031, d = 2.011$) and than male participants estimated the body weight of the self-similar ones ($M = 3.96$, $SD = 3.16$) ($t(57) = 4.392, p < .001, d = 3.106$). Despite large mean differences, we did not find a significant difference in body weight estimation of generic virtual bodies between men and women ($M = 4.73$, $SD = 5.19$) ($t(57) = -2.276$, $p = .116$). We found no effect of having motor control. Overall, we confirmed hypothesis H2.2, but not H2.1.

Active Modification Task (AMT) For AMT current, the percentage difference between one's current body weight and one's estimated current body weight, our calculations showed a main effect of self-similarity ($F(1,55) = 8.223, p = .006, \eta_p^2 = 0.130$). The participants underestimated their own body weight more when estimating generic virtual humans than when estimating self-similar ones. We found no effect of having motor control and no interaction effect. Furthermore, male participants ($M = -9.64$, $SD = 8.49$) underestimated their own body weight more than female participants ($M = -3.03$, $SD = 7.21$) ($F(1,55) = 11.185, p = .001, \eta_p^2 = 0.169$). For AMT ideal, the percentage difference between one's current body weight and one's estimated ideal body weight, our calculations revealed a significant interaction effect between having motor control and self-similarity

Table 3: The table shows the descriptive values for each experimental condition and p-values of the main and interaction effects for the factors motor control (MC / non-MC) and self-similarity (SS / non-SS) for the ANOVA models. Statistical significance indicators: $^{*}\ p < 0.05$; $^{\dagger}\ p < 0.01$; $^{\ddagger}\ p < 0.001$.

	SS - MC	non-SS - MC	SS - non-MC	non-SS - non-MC	Main E.	Main E.	Interaction E.
	M (SD)	M (SD)	M (SD)	M (SD)	SS	MC	SS & MC
Sense of Embodiment							
VEQ Virtual Body Ownership	4.88 (1.35)	3.97 (1.62)	4.34 (1.23)	3.38 (1.32)	$p < .001^{\ddagger}$	$p = .090$	$p = .860$
VEQ Agency	5.86 (0.91)	5.76 (1.08)	2.68 (1.36)	2.03 (1.18)	$p < .001^{\ddagger}$	$p < .001^{\ddagger}$	$p = .009^{\dagger}$
VEQ+ Self-Location	3.83 (1.42)	3.17 (1.34)	3.18 (1.45)	2.67 (1.51)	$p < .001^{\ddagger}$	$p = .116$	$p = .498$
Self-Identification							
VEQ+ Self-Attribution	4.83 (1.55)	3.64 (1.44)	4.15 (1.26)	3.11 (1.26)	$p < .001^{\ddagger}$	$p = .064$	$p = .655$
VEQ+ Perceived Self-Similarity	5.78 (0.78)	3.58 (1.59)	5.71 (1.05)	3.89 (1.33)	$p < .001^{\ddagger}$	$p = .633$	$p = .325$
Eerieness							
UVI Eerieness	2.76 (0.47)	2.55 (0.66)	2.73 (0.59)	2.71 (0.37)	$p = .265$	$p = .165$	$p = .221$
Passive Estimation Task (PET)							
PET $\overline{M}$ in %	2.27 (1.11)	5.37 (1.51)	1.88 (0.84)	3.41 (1.47)	$p < .001^{\ddagger}$	$p = .468$	$p = .376$
PET $\overline{A}$ in %	4.62 (4.50)	6.83 (7.09)	3.64 (3.21)	5.23 (6.82)	$p < .001^{\ddagger}$	$p = .454$	$p = .693$
Active Modification Task (AMT)							
AMT Current in %	-3.87 (9.66)	-6.45 (9.46)	-3.76 (6.43)	-6.10 (6.54)	$p = .006^{\dagger}$	$p = .775$	$p = .719$
AMT Ideal in %	-11.40 (10.96)	-10.66 (10.29)	-8.67 (9.81)	-11.49 (8.15)	$p = .187$	$p = .633$	$p = .045^{*}$

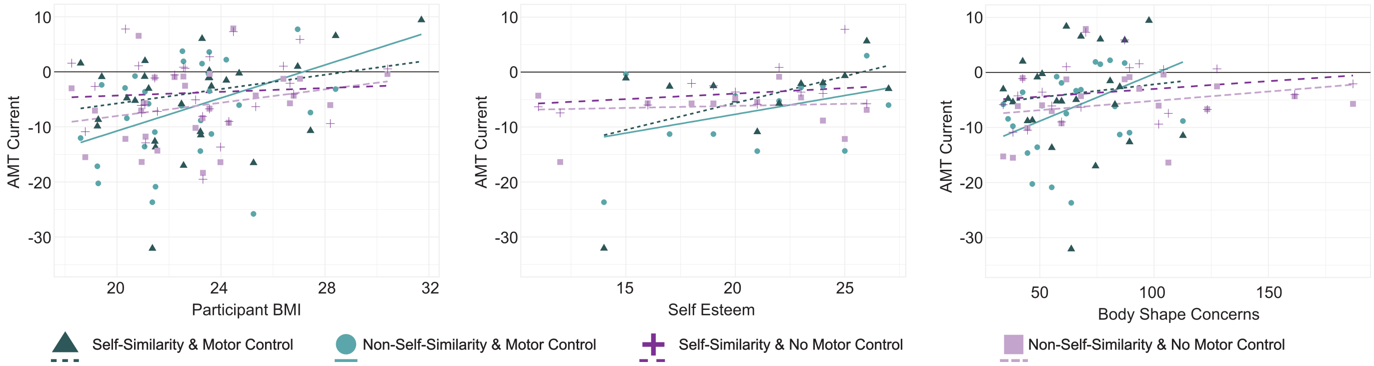

Fig. 4: The figure shows the influences of the participant's BMI (left), self-esteem (center), and body shape concerns (right) on AMT current for each condition.

($F(1,55) = 4.212, p = .045, \eta_p^2 = 0.071$). Post-hoc T-tests with Tukey correction showed a tendency for the ideal body weight to be estimated lower for generic non-controlled virtual humans than for self-similar non-controlled ones ($t(57) = 2.449, p = .079, d = 2.764$). We found no main effects. Overall, we confirmed hypothesis H2.2, but not H2.1.

4.2.2 Influence of the Participant's Body

The calculated multiple linear regression showed only tendencies of an influence of the participant's BMI on PET $\overline{M}$. We also found tendencies for an influence of the participant's BMI interacting with having motor control on PET $\overline{A}$. The multiple linear regression of AMT current revealed that the participant's BMI significantly predicted AMT current with the regression equation AMT current $= -38.39 + 1.4 \cdot \text{BMI} - 0.65 \cdot (\text{BMI} \cdot \text{Self-Similarity}) + 0.69 \cdot (\text{BMI} \cdot \text{Motor Control})$. The influence of BMI on AMT current is shown in Fig. 4 (left). We found a significant multiple linear regression model for the AMT ideal but no significant effect from any of the included factors. Overall, we could not confirm hypothesis H2.3.

4.2.3 Influence of the Participant's Body Image

We found no multiple linear regression model for PET $\overline{M}$ and PET $\overline{A}$. The regression for AMT current showed that it was significantly predicted by the participant's self-esteem and body shape concerns, with the equation AMT current $= -32.79 + 0.81 \cdot \text{RSES} + 0.13 \cdot \text{BSQ} + 0.15 \cdot (\text{RSES} \cdot \text{Self-Similarity}) + 0.61 \cdot (\text{RSES} \cdot \text{Motor Control}) - 0.03 \cdot (\text{BSQ} \cdot \text{Self-Similarity}) + 0.08 \cdot (\text{BSQ} \cdot \text{Motor Control})$. The influence of both on AMT current is shown in Fig. 4 (center and right). We found no multiple linear regression model for AMT ideal.

4.3 Qualitative Interview

We analyzed the interviews using an inductive approach, clustering responses on sticky notes in line with a semantic thematic analysis [3]. However, we did not conduct a full thematic analysis. We focused on Phases 3 and 4 (searching for and reviewing themes) to identify patterns in how participants perceived the virtual humans across experimental conditions. The following sections summarize the most frequently and most interesting mentioned themes for each condition.

Self-Similar Controlled Virtual Human Thirteen participants found the virtual human realistic due to its appearance and synchronized movements. Five noted the appearance was realistic but felt the mirrored movements were artificial directly compared to their real body due to small inaccuracies in movement.

Generic Controlled Virtual Human Seventeen participants reported the virtual human mirrored their movements but did not match their appearance. Five reported less self-identification due to the lack of self-similarity compared to observing the self-similar, controlled virtual human, though they did not find the scenario unsettling. Two accepted the virtual body due to movement synchronization, while one noted slightly noticeable movement delays due to the visibility of their own real body.

Self-Similar Non-Controlled Virtual Human Eleven participants observed that the virtual human had their appearance but moved independently, which three participants found strange to see themselves from a third-person perspective. Another five found this new perspective interesting, while three noted no significant differences from observing the generic, non-controlled virtual human.

Generic Non-Controlled Virtual Human Seven participants felt unrepresented by the virtual human because of its different appearance and movements. Four found the scenario unremarkable, and three noted no significant difference from observing it.

Table 4: The table shows the multiple regressions calculated for the influence of the participant's body and body image on the body weight perception tasks. Statistical significance indicators: $^* p < 0.05$; $^\dagger p < 0.01$; $^\ddagger p < 0.001$.

	PET $\overline{M}$	PET $\overline{A}$	AMT Current	AMT Ideal
Influence of Participant's Body				
Overall Model	$F(5,112) = 3.41, p = .007^\dagger$	$F(5,112) = 2.12, p = .068$	$F(5,112) = 3.00, p = .014^*$	$F(5,112) = 2.37, p = .044^*$
Participant's BMI	$t(112) = -1.81, p = .074$	$t(112) = -0.08, p = .940$	$t(112) = 3.23, p = .002^\dagger$	$t(112) = -0.86, p = 0.104$
Participant's BMI * Self-Similarity	$t(112) = 0.28, p = .782$	$t(112) = 0.98, p = .336$	$t(112) = -1.28, p = .202$	$t(112) = -0.01, p = 0.995$
Participant's BMI * Motor Control	$t(112) = -0.65, p = .517$	$t(112) = -1.89, p = .061$	$t(112) = -1.36, p = .176$	$t(112) = -0.51, p = 0.613$
Influence of Participant's Body Image				
Overall Model	$F(8,109) = 1.42, p = .196$	$F(8,109) = 1.04, p = .412$	$F(8,109) = 2.36, p = .021^*$	$F(8,109) = 1.56, p = .146$
RSES	-	-	$t(109) = 2.20, p = .029^*$	-
RSES * Self-Similarity	-	-	$t(109) = 0.35, p = .729$	-
RSES * Motor Control	-	-	$t(109) = -1.42, p = .160$	-
BSQ	-	-	$t(109) = 2.37, p = .019^*$	-
BSQ * Self-Similarity	-	-	$t(109) = -0.552, p = .582$	-
BSQ * Motor Control	-	-	$t(109) = -1.40, p = .163$	-

5 Discussion

In this work, we applied prior VR research on the design of virtual humans to AR systems, allowing users to interact with the real world while engaged. We focused on how having motor control over the virtual human's movements and self-similarity in appearance impact the body weight perception of virtual humans in AR. Our results indicate that self-similarity strongly affects SoE and self-identification with a virtual human, whereas having motor control showed weaker effects than in VR (H1.1–H1.4). Having motor control did not significantly change body weight perception, but participants estimated the body weight of self-similar virtual humans more accurately (H2.1–H2.2). Regardless of both factors, participants' BMI, self-esteem, and body shape concerns consistently influenced the estimation accuracy (H2.3).

5.1 Sense of Embodiment and Self-Identification

We hypothesized that participants would experience a stronger SoE with controlled virtual humans than with non-controlled ones (H1.1). We found only partial support for this hypothesis. Having motor control had no significant effects on self-location, but trends suggested more substantial virtual body ownership with controlled virtual humans than with non-controlled ones. Furthermore, participants perceived stronger agency for controlled virtual humans. While the interaction between self-similarity and having motor control complicated the interpretation of the agency effect, post hoc T-tests indicated that the primary effect stemmed from having motor control, fitting our manipulation check. Our effects of SoE measured were lower than those from a similar VR study by Wolf et al. [64], who analyzed SoE for generic virtual humans also using the VEQ [46]. The lower level of immersion in our AR system compared to their VR system might explain this discrepancy [27, 48, 59]. The lower level of immersion can decrease virtual body ownership, as observed in prior work [55, 66]. Another key factor influencing SoE is the visibility of the participant's real body in AR systems, which may compete with the virtual body and reduces virtual body ownership. This may disrupt the sensory and cognitive integration needed to achieve an SoE comparable to that in VR systems.

Our results partially align with Genay et al. [16], suggesting that users can develop SoE with controlled virtual humans in AR systems. Further, Wolf et al. [62] reported higher virtual body ownership and agency toward a generic controlled virtual human compared to ours while also using a video see-through AR system, but comparable virtual body ownership while using an optical see-through AR system and the VEQ [46]. Conversely, our participants experienced slightly higher virtual body ownership and agency with a self-similar virtual human than those in a similar setting by Nimcharoen et al. [34], albeit using an optical see-through AR system.

We confirmed hypothesis H1.2, where self-similar virtual humans elicited a stronger SoE than generic ones, aligning with prior VR research [13, 55]. Consistent with Fiedler et al. [13], self-similarity in the virtual human's appearance not only increased virtual body ownership [55] but also levels of agency and self-location.

Contrary to hypothesis H1.3, having motor control did not influence self-identification with the virtual human. While perceived self-similarity was unaffected, controlled virtual humans showed tendencies of increased self-attribution, consistent with Fiedler et al. [13], who found a significant effect of having motor control on self-attribution but not on perceived self-similarity.

For hypothesis H1.4, we confirmed that self-similar virtual humans enhanced self-identification in self-attribution and perceived self-similarity, consistent with previous VR research [13, 47, 52].

The interviews underpinned this section's findings. Participants reported that self-similar textures and having motor control enhanced their self-identification, while mismatches led to detachment.

Overall, our results highlight the potential of having motor control and self-similarity for future work to either boost or prevent users from associating themselves with a virtual human in AR systems. Moreover, the findings validate the successful experimental manipulation of having motor control and self-similarity, which is essential for further analyses of their effects on body perception. Future research should explore differences in SoE and self-identification mechanisms between VR and various AR systems, focusing on factors like level of immersion (e.g., influenced by the display type) and the influence of the participant's real body. Investigating these elements systematically could help optimize AR systems to match VR in delivering embodiment experiences.

5.2 Body Weight Perception

5.2.1 Influence of Self-Similarity, Motor Control and Gender

To examine the impact of having motor control on virtual human body weight perception, we hypothesized that participants would be less accurate in estimating controlled virtual humans' body weight than non-controlled ones (H2.1). However, we found no significant effect of having motor control on PET $\overline{M}$, PET $\overline{A}$, and AMT current, failing to replicate VR research findings [14, 33, 64]. This may be related to our finding that having motor control over the virtual human's movements per se had a weaker influence than in previous VR studies.

Further, we hypothesized that self-similarity influences virtual humans' body weight estimation accuracy (H2.2). Our findings support this hypothesis, showing more accurate estimates for self-similar virtual humans in PET $\overline{M}$, PET $\overline{A}$, and AMT current. This aligns with prior VR research [14, 38, 52] but contrasts with Mölbert et al. [32], where self-similarity led to greater misestimation.

Wolf et al. [63] compared body weight estimation of self-similar non-controlled virtual humans across VR and AR systems. Unlike our PET results, where participants overestimated body weight, their participants accurately estimated it using a video see-through AR HMD in a similar task. However, our findings align with their results from optical see-through AR HMDs. Additionally, our AMT current results are consistent with Nimcharoen et al. [34], where participants slightly underestimated their own weight when interacting with self-similar controlled virtual humans. Overall, the display's specifications (e.g., passthrough mode, resolution, field of view, refresh rate) seem to influence virtual human body weight perception. Future research should investigate which display-related factors most significantly affect it.

In addition to our manipulated factors, we analyzed gender differences, as previous studies suggest an influence on body weight estimation [6, 22]. In PET $\overline{M}$, women consistently estimated virtual human body weight more accurately than men, though both genders tended to overestimate. In PET $\overline{A}$, men were less accurate at estimating the body weight of generic virtual humans. In AMT current, women again estimated more accurately, while both genders underestimated their own body weight. Overall, men had more difficulty estimating body weight, while women were more sensitive to weight changes, particularly for generic virtual humans. This aligns with Thaler et al. [52] and may be because body weight is a more significant concern for women [22]. Although noteworthy, this is not the focus of our work, and future research should investigate further.

5.2.2 Influence of the Participant's Body

We could not confirm hypothesis H2.3, which posited a higher influence of participants' body weight on body weight estimation when they assessed controlled or self-similar virtual humans. As in previous VR work [14], regardless of having motor control or self-similarity, participants' BMI consistently affected body weight estimation in AMT current and showed similar tendencies in PET $\overline{M}$. This contrasts with other studies that found specific effects of self-similarity [51] and having motor control [64] on the influence of the participant's BMI on virtual human body weight estimation. Prior AR research indicates that the influence of BMI also varies with the type of display used. While Wolf et al. [62] found no effect when using an optical see-through AR system, they observed an influence when using a video see-through AR system [61]. As mentioned, future research should explore which display-related factors significantly influence virtual human body weight estimation.

The consistent influence of participants' BMI across all conditions might result from matching attributes like gender, height, or body shape with the virtual human in our study. For instance, Piryankova et al. [38] found that self-similar body shapes slightly affect the perception of a virtual human's body weight. Thus, omitting self-similarity in texture and motor control over the virtual human's movements may not be sufficient to eliminate the influence of one's own BMI on body weight estimation. Future research should examine how various self-similarity aspects, such as height, gender, texture, and shape, might influence the relationship between the participant's BMI and body weight estimation.

5.2.3 Influence of Participant's Body Image

We investigated how participants' self-esteem and body shape concerns affected their perception of body weight. Our study found a significant relationship between these factors and body weight perception for AMT current, contrasting with Thaler et al. [52], who found no such influence. However, our findings align with prior work [60], showing that higher self-esteem leads to more accurate estimations of one's own body weight (see Fig. 4, middle). Interestingly, higher body shape concerns also led to better estimation (see Fig. 4, right).

Visual analysis of half-violin plots of all body weight estimation accuracies in Fig. 3 shows noticeable variance differences in body weight estimation for AMT current and AMT ideal, likely influenced by having motor control. Estimates for non-controlled virtual humans were less scattered, while those for controlled virtual humans showed greater variance. This indicates that having motor control may affect body weight perception despite our data's lack of significant effects. A possible explanation could be the theory of double standards, where people apply stricter criteria to evaluate their own bodies compared to other bodies [54]. Thus, the estimates of non-controlled virtual humans may have been more objective and interindividual similar, explaining the lower variance. In contrast, the assessment of controlled virtual humans might have incorporated more personal, interindividual differences in attitudes, e.g., self-esteem and body shape concerns, toward one's own body, explaining the greater variance [5, 14]. However, these observations are preliminary and descriptive; further research is required to investigate the effects of double standards.

5.3 Summary

Our study highlights the crucial role of self-similarity in shaping the accuracy of virtual human body weight estimation, whereas the influence of controlling the virtual human's movements appears minor. This finding is consistent with the weaker impact of having motor control on SoE compared to similar VR studies. Furthermore, our results emphasize the key role of self-similarity in shaping the perception of virtual humans in AR systems and offer design guidelines to purposely enhance or prevent SoE and self-identification to virtual humans. It also shows that having motor control has less impact on SoE and self-identification than similar VR studies, likely due to the integration of the real environment which exposes the participant's own body. This visibility can lead to noticeable delays between real and virtual body movements during interactions with a controlled virtual human, as there is no motion-to-photon latency with one's own real body, diminishing SoE and self-identification. As also mentioned in the interviews, these delays are more pronounced in AR than VR and can substantially affect the perception of virtual humans. Zoulias et al. [65] pointed out that even minor timing discrepancies, particularly when tactile feedback precedes visual signals, can disrupt the immersive experience.

These characteristics may affect the perceived plausibility and, thus, the estimation of a virtual human's body weight. Skarbez et al. [48] and Wienrich et al. [59] highlight the need for external coherence in AR systems, where virtual objects should interact predictably with real ones. For example, a virtual mirror should reflect a participant's movements precisely simultaneously, and a virtual human who (does not) look like the participant should (not) follow their movements. Maintaining a realistic representation is essential in AR to influence how virtual objects, including human bodies, are perceived. In contrast, VR systems focus more on internal coherence [48] or reference frames [59], facilitating movement control of diverse virtual personas and acceptance of varied body representations. The threshold for suspension of disbelief, the ability to accept virtual experiences as real, differs between AR and VR environments [19, 27, 59]. In AR systems, mismatches between the user's real and virtual body may lead to quicker dissonance and reduced plausibility, potentially affecting observed effects of SoE, self-identification, and body weight perception. This argument is supported by Wolf et al. [63], who demonstrated a significant effect of incongruence when viewing a rendered virtual human in a real environment compared to one in a virtual environment.

5.4 Limitations and Future Work

Firstly, the visibility of one's own body appears to influence the effects of SoE, self-identification, and body weight perception toward the virtual human, which we cannot fully assess. Future AR studies should specifically explore this influence. Alternatively, an AR system that can hide one's own real body would be conceivable, e.g., by overlaying the real body [39] or a masked-out real body [25].

Secondly, the ethnic dissimilarity between participants and the white-only generic virtual humans may have an influence. Recent research by Do et al. [8], published after the study was conducted, underscores the need to consider ethnic diversity in future research.

Thirdly, our evaluation can only be compared with partially comparable VR studies to determine if VR effects are transferable to AR systems, as we did not collect comparative VR data ourselves. Future research should focus on study designs that enable direct comparisons between VR and AR systems.

Fourth, our sample is gender-imbalanced, which may have influenced the observed gender effects. Gender was included as a control variable, as it has been shown to affect body weight estimation generally [6, 22] and in VR contexts [33, 52]. However, this was not the primary focus of our study. Future research should explore the role of gender in body weight perception in AR more closely.

Finally, we investigated virtual body perception in AR to assess the transferability of VR effects. While our study was motivated by mental health, it was not designed for therapeutic use. Future work should apply these findings in treatments for body image disorders.

6 Conclusion

Our presented work contributes to the understanding of body weight perception of virtual humans in AR systems, examining whether the advantage of AR, including the real environment, can be fully utilized or if it comes with limitations impacting body weight perception. We highlight the importance of self-similarity in appearance and having motor control over the virtual human's body movements in shaping this perception. Our results indicate that especially self-similar virtual humans notably improve users' sense of embodiment, self-identification, and body weight estimation accuracy. However, we noted that the effects of having motor control are less pronounced compared to VR systems, likely due to the mixed reality setting and the visibility of the user's real body alongside the virtual one. These insights are relevant for therapeutic applications of body image disorders, as they demonstrate that using self-similar virtual humans with modifiable body weight not only evoke a sense of embodiment and self-identification but also enhances the user's body weight perception in AR settings. Nonetheless, our study highlights the need for further research to clarify the unique effects of AR settings on body weight perception and to embed our results in an appropriate therapeutic setting, considering factors such as coherence with the real environment.

Supplementary Materials

All supplementary materials are available on OSF (https://osf.io/9ntuw/) under a CC BY-SA 4.0 license, including (1) study data, (2) ANOVA results for sense of embodiment, self-identification, eeriness, and body weight estimation tasks, and (3) the full paper.

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