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Improving Social Acceptance of Orthopedic Foot Orthoses Through Image-Generative AI in Product Design

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Abstract: The lack of social acceptability for wearable devices such as orthopedic foot orthoses can lead to irregular usage and missed health benefits, as shown in prior studies. While AI-generated designs have been explored for prototyping aesthetic hand orthoses, their impact on social acceptability, particularly for foot orthoses, remains unknown. The current state of research is limited, as no empirical evidence exists on whether AI-designed orthoses influence acceptance, nor has the role of customized generative pre-trained transformers (GPTs) and specific prompting strategies been examined in this context. To address these gaps, we conducted two mixed-methods studies to investigate (1) the impact of AI-generated orthosis designs on social acceptability compared to existing orthopedic products and development concepts and (2) how a customized GPT and different prompt keywords influence acceptance. Our results show that AI-generated designs significantly enhance social acceptance across orthotic categories. Furthermore, we found that personalized GPTs and targeted prompt keywords significantly influence user perception. Overall, our findings highlight the potential of using AI to create socially acceptable design solutions for wearable technology and offer new applications for future smart devices. We contribute to generative AI in product design and provide concrete recommendations for optimizing prompting strategies to enhance social acceptance.

Keywords: artificial intelligence; generative AI; chatGPT; text-to-image; human-centered design; human–computer interaction; product design; social acceptance; foot orthoses; wearables

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1. Introduction

Orthopedic foot orthoses are standardized devices that are essential for the rehabilitation of patients recovering from injuries or managing chronic foot diseases [1]. The designs of these assistive devices differ, featuring orthoses with varying leg lengths, bandages, and foot drop orthoses, each customized for particular medical purposes [2]. Each category of orthotic products is designed to support patients with different medical needs and mobility requirements [3]. This product diversity requires highly personalized designs to meet the specific demands of different health conditions and patient preferences [4]. While technical function is essential for medical effectiveness, aesthetics and usability are also key elements in the design of orthopedic foot orthoses to promote patient acceptance and support successful use and rehabilitation outcomes [2]. For example, a study by

Ghoseiri and Bahramian [5] investigated user satisfaction with orthotic devices among 293 participants, revealing that concerns related to the appearance of the devices often resulted in low satisfaction rates. Furthermore, a systematic literature review by Swinnen and Kerckhofs [6] analyzed ten studies involving 1576 patients and highlighted the critical role of aesthetics in the compliance of wearing lower limb orthotic devices. The review found that a notable number of patients avoid wearing their devices regularly due to their "cosmetically unacceptable" appearance, highlighting the "large importance" of aesthetics in patients' decisions to wear these devices. This underscores the significant impact of aesthetics on device adoption and user perception [7]. However, the design processes of these standardized devices frequently rely on traditional methods that limit adaptability and patient involvement, leading to compliance issues [8]. This dissatisfaction can lead to inconsistent use of standardized orthopedic aids and missed health benefits, as highlighted by previous work [9].

Current advancements in sensor technology offer the potential to transform these conventional orthoses into smart products, commonly known as wearable electronic devices, which can monitor specific health parameters [10]. In theory, the creation of smart orthotic footwear could enhance the rehabilitation process by enabling the continuous monitoring of various conditions while also extending health benefits [11]. However, the conceptual development and integration of such advanced technologies also bring new challenges for product design that must be addressed to ensure patient acceptance in line with medical requirements [12].

A systematic literature review by Orlando et al. [13] highlighted that there is a significant need for improvement in lower extremity orthotic devices. A list of five main user needs (function, expression, aesthetics, accessibility, and other) and the corresponding subitems for the use of lower limb orthoses was compiled. It was concluded that improvements in the design, prescription, and implementation of these devices are crucial to improve utilization and achieve greater user satisfaction. Therefore, incorporating user perspectives and identifying their needs in the development process is essential to ensure a high level of user acceptance for smart technologies. For example, Van der Wilk et al. [14] applied a user-centered design approach and conducted a qualitative study with eight participants in focus groups to investigate patients' perspectives on improving the design of an ankle foot orthosis (AFO). The three main themes identified by the patients, *walking and standing ability*, *activities*, and *AFO characteristics*, were highlighted as the most relevant aspects for future developments.

To address these design challenges, the use of image-generative artificial intelligence (AI) applications in the design process of future developments presents a novel approach [15]. As shown by Suessmuth et al. [16], generative AI can support concept creation in footwear design by actively involving users in the design process and tailoring products to their preferences, highlighting valuable potential for the industry. Building on this idea, the emerging trend of rapid image creation with tools such as DALL-E [17] from OpenAI provides new opportunities for generating design concepts based on user-defined prompts. The use of such technologies could support the iterative design process within the structured product development of orthopedic orthoses. However, the impact of AI-generated wearable designs on social acceptance remains an open question. To address this research gap, we formulate the following three research questions (RQs):

- RQ1: How does the use of AI-generated designs impact the perceived social acceptability of foot orthoses compared to conventional orthopedic products or research developments?

- RQ2: How does the category of orthotic products influence the social acceptance of foot orthoses, comparing categories such as short-leg orthoses, high-leg orthoses, foot bandages/textiles, and foot drop orthoses?
- RQ3: How does a custom generative pre-trained transformer (GPT), trained on data for personalized orthoses, impact social acceptance, and what effect do specific keywords in the prompt structure (such as "social acceptance" or "sporty design") have on this acceptance?

While aspects such as biocompatibility and manufacturability are critical in the development of orthopedic devices, our study focuses on the visual perception and social acceptance of AI-generated designs. These factors are particularly relevant for end users, whereas material and production requirements fall within the domain of technical experts, who were not the target group of this study. In addition, current generative AI models are primarily suitable for the conceptual phase of designs, as they are generally unable to take technical manufacturability into account, which is why specialized technical expertise is required [18].

Therefore, we conducted two studies to investigate the influence of AI-generated orthoses designs on social acceptance. The first study aimed to assess the potential of AI integration by evaluating whether AI-generated orthoses achieved higher acceptance ratings compared to conventional products. The second study compared the output of a custom GPT and ChatGPT-4 and investigated the effects of specific keywords in the prompts on acceptability ratings. Based on the findings, we provide recommendations for refining text prompts and discuss the implications of these enhancements for future developments in wearable design.

We aim to contribute to the field of human-centered design using generative AI by expanding the knowledge of socially acceptable smart foot orthosis (SFO) designs and investigating the role of image-generative AI in the product development process. Accordingly, this paper highlights the following three main contributions:

1. We introduce a novel approach that leverages image-generative AI to enhance the customization and aesthetic appeal of foot orthosis designs, increasing their alignment with user requirements and visual attractiveness.
2. Our research provides empirical evidence demonstrating that AI-generated orthosis designs significantly enhance social acceptability among users. This potential could be utilized to create widely accepted design solutions for other products as well.
3. We offer a comprehensive set of future recommendations for integrating AI into the orthotic design, aiming to refine the prompt design process to ensure that the resulting designs meet product requirements and patient design expectations.

2. Related Work

This section examines generative AI techniques, particularly text-to-image and image-to-image generation, and explores their potential applications in product design. Following this, we discuss how design influences the social perception of wearable devices. Finally, we summarize the identified research gaps and outline how our studies intend to contribute to this research field.

2.1. Generative AI: Image-to-Image and Text-to-Image Creation

Generative AI is a subset of AI that uses trained models from deep learning, a key component of machine learning, to generate new content from collected data. It employs trained multi-layer artificial neural networks that can identify patterns in datasets and make decisions for data generation. Therefore, the use of AI image-generation tools enables rapid prototyping from a simple sketch to a 3D prototype, whether virtual or physical [19].

One example is the image generation tool DALL-E from OpenAI, which is a separate tool from a GPT chatbot—ChatGPT—based on an large language model (LLM). DALL-E is a transformer model [20] and enables text-to-image or image-to-image generation via text or image prompts.

Text-to-image generation transforms textual information into pixel-based image data. This method can be used in product development to create initial concepts based on specific product requirements [21]. However, achieving appropriate outputs requires an iterative approach to prompt engineering. Therefore, White et al. [22] proposed a prompt pattern catalog to improve prompt engineering with ChatGPT. They stated that specifying personas and templates allows the model to adopt specific roles and ensures that output quality and consistency are tailored to user needs. Furthermore, they discussed prompt patterns for visualizations that enable ChatGPT to generate specific textual outputs, which can subsequently be used to create visualizations with tools like DALL-E. Additionally, a study by Liu and Chilton [23] highlighted the importance of prompt engineering in text-to-image generation and proposed guidelines to achieve better outcomes.

While text-to-image generation uses text input to create a visual output, image-to-image generation requires visual data from an existing image to create a visual output. The use of image-to-image generation is based on Generative Adversarial Networks (GAN) [24], which enable image generation through the interaction of two neural networks: a generator and a discriminator. This technology can be used to refine initial sketches or create design variations, improving the iterative design process.

2.2. Generative AI in Product Design

Image-generative AI enables new possibilities for designers in product development through creativity-expanding iterations of design sketches [25]. These tools could be used in the styling process for various applications [26–29]. However, the application of image-generative AI tools in the development of orthotic devices has not yet been realized.

Nonetheless, initial research projects demonstrate promising results from using AI throughout the design process, from initial concept to final manufacturing via 3D printing [30,31]. For example, Popescu [30] proposed *orthosis_GPT*, a custom version of ChatGPT trained with predefined configurations to support the preliminary design of a wrist–hand orthosis. Based on an iterative design process driven by prompt engineering, the wrist–hand orthosis was finally 3D-printed. This workflow illustrates the potential of using AI in the creation of orthosis designs and subsequent processing for 3D printing. Furthermore, Bartlett and Camba [31] presented examples of generative AI in product design, showcasing the creation of shoes with DALL-E. The generated image output was used by designer Kedar Benjamin to overlay the topology onto this image with additional software and to create a 3D model for 3D printing. Finally, a significant limitation identified was that although the printed versions appeared similar, manual input from designers was necessary to create a topologically optimized 3D model. Additionally, Chiou et al. [25] conducted a study with six designers to explore the collaboration between designers and generative AI in creating new ideas. It was shown that AI image generation offers new possibilities for artistic expression and inspiration with great potential for future contributions in the design field. However, the study also highlighted future challenges and raised questions about copyright and social justice. In conclusion, these studies established a novel approach for creating AI-based designs that meet user requirements and enable the progression from initial design to final 3D printed prototypes.

2.3. Influence of Design on the Social Perception of Wearable Devices

In the field of Human-Computer Interaction (HCI), the influence of factors such as social perception and comfort on wearable devices is extensively researched [32–35]. Research demonstrates across multiple studies that design is crucial for the acceptance and continued use of wearables [36–38]. For instance, a focus group study by Canhoto and Arp [37] investigated the influence of factors for the sustainable use of various Internet of Things (IoT) health and fitness wearables. The study showed that designing distinctive devices enhances visibility, which influences user acceptance and encourages them to continue wearing the device. In addition, Adapda et al. [39] found that social acceptance can vary greatly depending on the type of smart device as well as the user group. Furthermore, Liao et al. [40] showed that smart insoles placed in shoes received the highest comfort ratings compared to other electronic wearable devices that were directly attached to the body. However, social acceptance can be influenced by various factors, including gender and cultural aspects [33]. Therefore, designers must consider a wide range of user preferences to develop widely accepted product designs.

In HCI research, several standardized questionnaires exist for the measurement of social impact from interactive and ubiquitous wearable technologies (e.g., Technology Acceptance Model (TAM) [41], Unified Theory for Acceptance and Use of Technology (UTAUT) [42], Stereotype Content Model (SCM) [43], or the Wearable Acceptability Range (WEAR) [44]). For instance, Davis et al. [41] proposed the TAM model, which was later updated to TAM 3.0 by Venkatesh and Bala [45], an enhanced version for a more comprehensive user understanding of technology adoption. In order to summarize various competing models with differing acceptance factors, Venkatesh et al. [42] compared eight models for measuring technology acceptance and validated UTAUT as a unified theoretical model. However, the literature indicates that while acceptance models such as TAM or UTAUT are suitable for evaluating technological acceptance itself, they are not "clearly applicable" to technologies that are directly worn on the body [36].

For this reason, the WEAR scale developed by Kelly [44,46] serves as an effective tool for measuring the social acceptability of wearable devices or prototypes. For example, Kelly and Gilbert [36] applied the WEAR scale in their study, demonstrating that medical necessity enhances the social acceptability of wearable devices, as it underscores the wearer's dependence on the device. However, they also highlighted the discrepancy in the literature between the stigmatization of medical devices and the recognized medical necessity of such assistive technologies. To address existing stereotypes and social perceptions, the SCM questionnaire by Fiske et al. [43] could be utilized, as it assesses these factors across two perceived dimensions: competence and warmth [47]. Previous work has applied this model to evaluate mobile devices [48] and has confirmed its effectiveness across different cultures [49]. A study by Sehrt et al. [50] utilized the SCM and WEAR scales to investigate the social acceptability of wearable devices based on their body location. The results showed that placement on the ankle received the lowest SCM ratings, indicating poorer acceptability compared to upper body locations. These findings support the statement that the social perception of wearable devices varies for different body locations [51–53]. Overall, the use of these questionnaires revealed current problems with the social acceptance of various devices and that better design is needed to achieve greater acceptance in the future.

2.4. Research Gaps

AI image generation opens up new possibilities for creativity, assisting designers in progressing from sketches to 3D models through text-to-image and image-to-image generation techniques. Initial studies have demonstrated that AI can be used effectively in product design by enabling the development of concepts such as wrist–hand orthoses and the subsequent 3D printing of prototypes. However, the impact of AI-generated aesthetic designs on the social acceptance of orthopedic foot orthoses remains unknown.

To evaluate stereotypes and social acceptance of wearables, the SCM and WEAR scales are often used as validated questionnaires. Previous research using these questionnaires has shown that wearables attached to the ankle typically receive lower acceptance rates compared to those worn on other body parts. Consequently, it remains unclear how orthopedic footwear is perceived by users and which aesthetic design adjustments are necessary to enhance acceptance for future smart developments.

By addressing these research gaps, we aim to contribute to the field of socially acceptable wearable orthopedic footwear design. Additionally, we aim to explore the potential of AI in future design processes to develop aesthetically acceptable design concepts. To this end, we conducted two studies to investigate the effects of AI-generated designs on the social acceptance of orthopedic footwear.

3. Materials and Methods

3.1. Study 1: The Impact of AI-Generated and Conventional Orthotic Designs Across Device Categories on Social Acceptability

To examine the influence of AI-generated orthotic designs on social acceptability, this study compared different AI-created designs with conventional orthopedic products and research-based developments. Additionally, we analyzed how various orthotic device categories affect acceptance. Social acceptability was quantitatively assessed using the WEAR scale, while stereotypical perceptions were evaluated through the SCM model, measuring warmth and competence ratings. To complement these findings, qualitative feedback provided deeper insights into user needs and preferences.

3.1.1. Study Design

A total of 161 participants were recruited through mailing lists via our institution and within personal networks. We conducted an online survey using a two-factorial within-subject design to investigate how different design types and product categories of orthopedic foot orthoses influence social acceptability. The two independent variables were DESIGN TYPE and ORTHOTIC CATEGORY. The variable DESIGN TYPE includes three individual levels: *Generative AI*, *Orthopedic products*, and *Development concepts*. The ORTHOTIC CATEGORY includes four levels: *Short-Leg Orthoses*, *High-Leg Orthoses*, *Foot Bandages/Textiles*, and *Foot Drop Orthoses*. We hypothesized that the perceived social acceptability of foot orthoses will be positively influenced by *Generative AI* concepts compared to the traditional *Orthopedic products* and *Development* concepts. We also hypothesized that the perception of acceptability would vary strongly within the ORTHOTIC CATEGORY, as different device types may elicit different user reactions depending on their design and visibility.

3.1.2. Stimuli

Four different categories of orthopedic foot orthoses (*Short-Leg Orthoses*, *High-Leg Orthoses*, *Foot Bandages/Textiles*, and *Foot Drop Orthoses*) were chosen to cover the medical needs of different foot conditions. We selected six different images for each ORTHOTIC CATEGORY, resulting in a total of twenty-four stimuli (see Figure 1).

Each ORTHOTIC CATEGORY included two images of *Generative AI* orthoses, two *Orthopedic products*, and two orthoses from *Development concepts*. The selection of two different orthoses for each DESIGN TYPE ensured a diverse representation of design variations within each ORTHOTIC CATEGORY. All images were presented with a white background and consistent positioning of the orthosis to ensure comparability. Adobe Photoshop version 2023 24.0.1 was used for manual adjustments, such as rotating the orthosis and creating a transparent background where necessary. Each image contained only the orthosis and some visible parts of the lower leg to maintain focus on the orthotic device itself.

Two approaches were used for *Generative AI* designs: text-to-image and image-to-image generation. Text-to-image generation was applied using DALL-E 3, which is based on a transformer architecture, from ChatGPT-4 [54] (OpenAI). Text prompts were created to design smart orthoses based on the type of orthosis and its medical functions. These typically feature a gray device color on a white background. Additionally, the prompts were extended to include small black boxes on the sides of the orthoses, which serve as placeholders for electronic components to enable smart functions. For image-to-image generation, images of medical orthoses were used as prompts to create realistic designs. The following prompt was used and iteratively refined during re-prompting: "*Generate an image of a foot orthosis based on the shape of the reference image. The orthosis should provide full protection for the lower leg and foot, consisting of two rigid housing parts that enclose the leg and are secured with Velcro straps. The orthosis should be gray and displayed against a white background. Additionally, a small box should be integrated into the orthosis to house sensors for smart functionalities*". The images of *Orthopedic products* are based on standardized medical devices that are available in online shops or medical supply stores: *VACOpedes* [55], *AIRCAST® AIRSELECT™ Short Walker* [56], *VACOcast Diabetic Boot* [57], *AIRCAST® AIRSELECT™ Achilles Walker* [58], *FastProtect Malleo* [59], *The BetterGuard* [60], *WalkOn Reaction Lateral* [61], and *ofa Push ortho Fußheberorthese AFO* [62]. These products are currently used by patients with foot conditions and represent state-of-the-art solutions. The *Development concepts* stimuli include various devices proposed in research projects [63–66], 3D-printed prototypes published on the web [61,67,68], and a self-created 3D CAD-design (C4-DEV2).

Figure 1. Overview of the 24 stimuli used in the online survey, categorized by the two independent variables DESIGN TYPE and ORTHOTIC CATEGORY. The stimuli are arranged horizontally by the four orthotic categories, *Short-Leg Orthoses*, *High-Leg Orthoses*, *Foot Bandages/Textiles*, and *Foot Drop Orthoses*, and vertically by the three design types, *Generative AI*, *Orthopedic products*, and *Development concepts*.

3.1.3. Procedure

The study was conducted in accordance with the ethical standards for user studies as required by our institution and received ethical approval from the German Society for Nursing Science (No. 23-027). Participants were informed about the study's purpose, ethical procedures, data privacy, data anonymity, and the intended use of their data before participation. Informed consent was obtained via the online platform before the start of the survey. Participants received a web link to our landing page, where they could access the online survey, which was created using LimeSurvey. After signing the informed consent form, participants were asked about demographic data, information about past conditions, and prior knowledge of orthopedic footwear or smart orthoses. Following this, participants received a brief introductory text for each orthotic category to prevent major misinterpretations and to provide context for the device and medical application. Participants were then presented with the 24 stimuli in a randomized order. For each stimulus, the corresponding picture was shown, and participants rated two statements about social acceptance and aesthetic design expectations on a 7-point Likert scale. The questions were "*To which extent do you agree with the statement that the device is socially accepted?*" and "*To what extent does the design meet your aesthetic expectations?*", with responses ranging from *totally unacceptable* (1) to *perfectly acceptable* (7). In addition to the quantitative questions, qualitative feedback was obtained via a free text entry question for each stimulus: "*What positive/negative aspects of the orthosis do you notice?*". Following this, the standardized SCM and WEAR questionnaires were completed for each stimulus. After answering all 24 conditions, participants responded to concluding questions regarding any changes in their perspective on orthoses, noting positive aspects, negative aspects, prior knowledge of AI image generation, and any additional feedback. The average completion time for this survey was 75 min.

3.1.4. Measures and Data Analysis

In this study, we used a mixed methods approach based on quantitative and qualitative feedback. Quantitative data were measured using the SCM and WEAR scales, complemented by two seven-point Likert items assessing social acceptance and aesthetic design expectations. These data were analyzed through descriptive and inferential statistics. Additionally, qualitative feedback derived from participants' free-text responses was assessed using thematic analysis. The methods and data analysis procedures are described in detail in the following paragraphs.

Quantitative: Stereotype Content Model (SCM)

The SCM questionnaire by Fiske et al. [43] was used to assess stereotypes and social perceptions of various foot orthoses based on two perceived dimensions: warmth and competence. This standardized questionnaire consists of nine items rated on a 5-point scale ranging from *not at all* (1) to *extremely* (5). The competence dimension was evaluated using five items (*competent*, *confident*, *independent*, *competitive*, and *intelligent*), each assessed by the question "*As viewed by society, how … are members of this group?*". Additionally, the same question was used to assess the warmth dimension, consisting of four items: *tolerant*, *warm*, *good-natured*, and *sincere*. For the data analysis, a two-factorial repeated measures (RM) ANOVA was used.

Quantitative: Wearable Acceptability Range (WEAR)

To measure the social acceptability of wearable technology, the WEAR scale by Kelly [44] was used. The WEAR scale (version 3) consists of 14 items, each rated on a 6-point scale ranging from *strongly disagree* (1) to *strongly agree* (6). Five of these 14 items are reverse-scored. The total score was divided by 14 to obtain an average score, which can be graded from *extremely low social acceptance* (1) to *extremely high acceptance* (6). An RM ANOVA was used for data analysis, similar to the procedure used for the SCM scale.

Quantitative: 7-Point Likert Scales

As described previously in Section 3.1.3, two questions were used to rate statements about social acceptance and aesthetic design expectations on 7-point Likert scales. For the evaluation, a non-parametric Aligned Rank Transform (ART) RM-ANOVA was applied.

Qualitative Feedback

Qualitative results from the free text entries were assessed using inductive thematic analysis [69]. Anonymized data were transcribed, coded, and analyzed paragraph-wise to identify categories and main themes. Two researchers were involved in the data analysis process: one researcher transcribed and coded the data set independently, while the second researcher reviewed the results for consistency.

3.2. Study 2: The Impact of GPT Customization and Prompt Keywords on the Social Acceptability of AI-Generated Orthotic Designs

Based on our first study, which showed that AI-generated designs can increase the social acceptance of orthopedic foot wearables, this study further explored the role of prompt customization in shaping user perception. In particular, the first study revealed that high-leg orthoses received the lowest acceptance ratings. Therefore, we examined which factors in AI image generation could positively influence the acceptance of this device category. While the initial study confirmed the potential of generative AI for orthotic design, it also raised questions regarding the influence of specific keywords in the prompts used and the application of customized GPTs. Furthermore, it remained unclear how the inclusion of keywords related to user preferences would affect the perceived acceptability of designs. To address this, our second study investigated the impact of various keywords and the use of a personalized GPT tailored to specific patient and product requirements. Previous research has demonstrated the influence of prompt structures and provided recommendations for different user roles [22]. Building on this knowledge, we take one step further and contribute to user-centered prompting strategies by incorporating keywords that enhance the alignment between generated designs and user needs.

3.2.1. Study Design

In our second study, we conducted an online survey to investigate the effects of different prompt keywords and GPT personalization on the social acceptability of AI-generated high-leg orthosis designs. In total, 133 participants were recruited. The recruitment of participants was conducted similarly to the first study, using mailing lists of our institution and personal networks. A two-factorial within-subject design was carried out with the two independent variables: GPT and KEYWORD. The variable GPT has two levels: *ChatGPT* and *OrthoticFootGPT*. The variable KEYWORD has four levels: *No Keyword*, *Usability*, *Social Acceptability*, and *Sporty Design*. The hypothesis of our second study is that perceived acceptability will significantly vary depending on the specific keywords used in the prompts and that the inclusion of new keywords will positively influence this acceptability. Furthermore, we hypothesize that a customized GPT will lead to more acceptable perceived outcomes compared to the standardized model.

3.2.2. Stimuli

The model GPT-4 from ChatGPT was used to create the stimuli of high-leg orthoses, which allows the creation of a custom GPT that can be configured according to the desired response and outputs. DALL-E 3 image generation was activated in the configuration interface of the customized GPT, and specific knowledge and instructions were provided as input. However, OpenAI does not disclose specific details about its training configuration or model architecture. The customized GPT named *OrthoticFootGPT* was described as a "generative design assistant to support the creation of socially acceptable foot orthoses". To generate a user-specific output, the knowledge base for the *OrthoticFootGPT* was customized with a comprehensive set of data tailored to high-leg orthoses. This dataset included

- Product specifications: Detailed information on the aesthetic and functional aspects of high-leg orthoses, such as material types, sizes and weight from data sheets and guidelines.
- Usage instructions: Documents with instructions and user manuals for the use and maintenance of these devices.
- Product images: Sample images of high-leg orthoses from various suppliers as a visual reference for a realistic design.
- Research articles: Related articles providing insights into product design rules, the concepts of accessibility/usability, and orthotic development were searched on Google Scholar.
- Keyword definitions: Documents based on international standards and dictionary definitions provided explanations about the three keywords (usability, social acceptability, and sport design) to guide the AI in generating contextually relevant content.

For both *ChatGPT* and *OrthoticFootGPT*, the following prompt was used as the foundation for image generation: "*Create a realistic image of a white-grey foot orthosis with a high shaft. The orthosis should have stabilizing properties so that it can be worn for longer periods during rehabilitation. The background should be white and only show the leg with the orthosis*". In addition, a sentence was added to the basic query for each keyword to tailor the images to the specific definition. For example, for social acceptability: "*The orthosis should ensure a high level of social user acceptance by offering an attractive aesthetic design and high wearing comfort*".

To ensure realistic product images and avoid misinterpretation or misleading details, the DALL-E editor interface was applied manually to ensure consistency across all images (e.g., by removing the second leg or unrealistic features). Similar to the first study, each image was manually adjusted using Adobe Photoshop to create transparent backgrounds and ensure consistent foot rotation angles. All generated images are shown in Figure 2 and the workflow for generating the visual stimuli is illustrated in Figure 3.

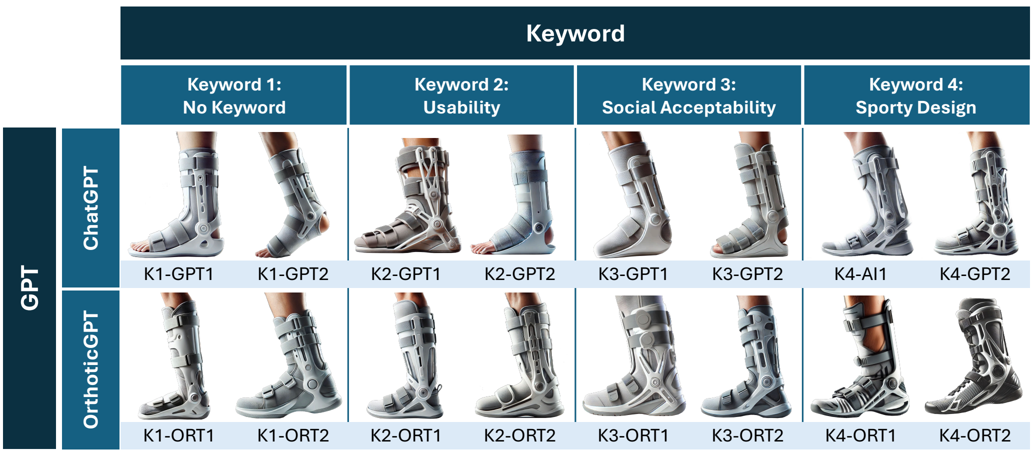


Figure 2. Overview of the 16 stimuli used in the online survey, categorized by the two independent variables, GPT and KEYWORD. The stimuli are arranged horizontally by the four keywords, *No Keyword*, *Usability*, *Social Acceptability*, and *Sporty Design*, and vertically by the two GPTs: *ChatGPT* and *OrthoticFootGPT*.

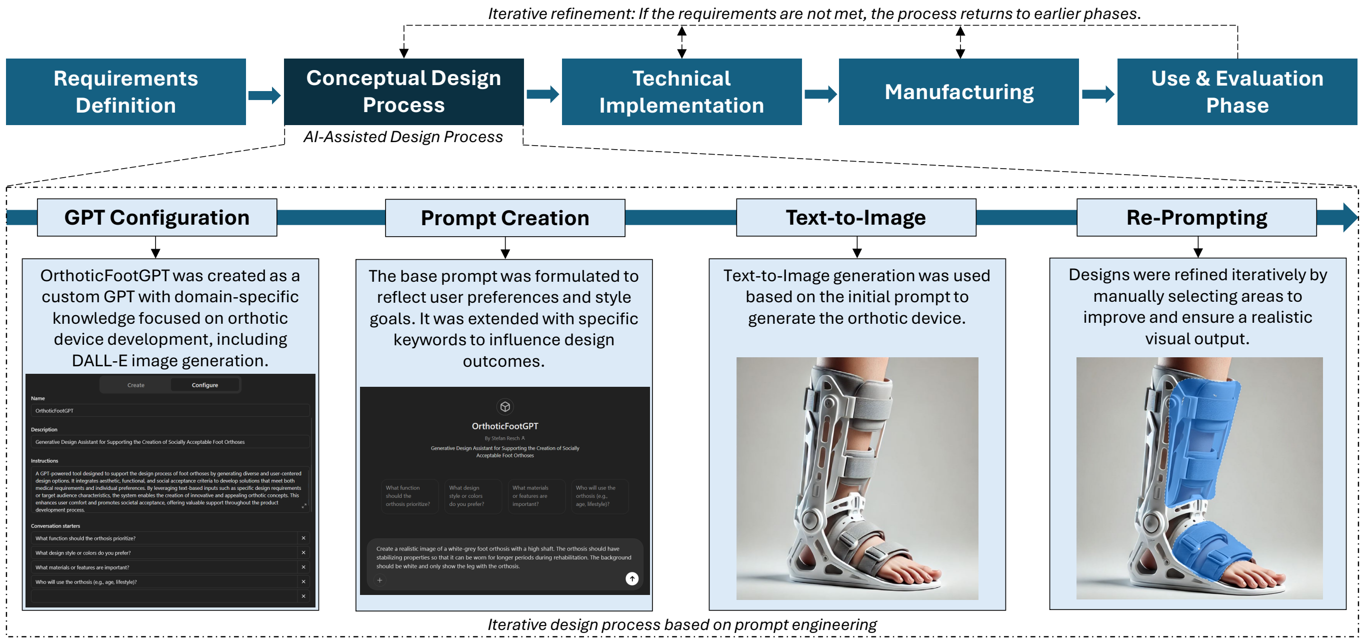


Figure 3. Schematic overview of the design generation workflow, including GPT customization, prompt creation, and text-to-image generation.

3.2.3. Procedure

The study procedure was identical to that of the previous study, including ethical approval by the German Society for Nursing Science (No. 23-027) and compliance with institutional ethical standards. As in the previous study, participants were informed about data privacy, anonymity, and the intended use of their data before providing informed consent via the online platform. Participants signed an informed consent form and provided demographic information along with details about their previous experience with image-generative AI. The 16 conditions were then presented in a randomized order. At the end of the survey, participants were asked to answer some open-ended questions about positive and negative aspects of the designs, as well as additional feedback. The average time to complete this survey was approximately 64 min.

3.2.4. Measures and Data Analysis

Similar to the first study, the quantitative data were collected using the standardized SCM [43] questionnaire, the WEAR [44] scale, and two 7-point Likert items to assess the social acceptance and aesthetic design expectations. Additionally, participants provided qualitative feedback through free-text responses about positive and negative aspects of the designs. The quantitative data analysis was conducted using descriptive and inferential statistics. Qualitative feedback was analyzed using inductive thematic analysis [69].

4. Results

4.1. Study 1

This section presents the characteristics of the study group (Section 4.1.1), followed by the evaluation of quantitative results (Section 4.1.2). This includes the Correlation of SCM and WEAR Ratings, assessments of Stereotype Content Model (SCM) and Wearable Acceptability Range (WEAR) data, as well as the analysis of Seven-Point Likert Scale ratings on device acceptance and aesthetic design expectations. The statistical analysis was performed in R using the package rstatix [70]. Qualitative results obtained through thematic analysis are documented in Section 4.1.3.

4.1.1. Participants

A total of 80 out of 161 participants (31 female, 48 male, and 1 divers) completed the online survey and were included in the data analysis. Participants' ages ranged from 19 to 77 years (M = 30.62, SD = 13.69). The participants had diverse educational backgrounds and came from seven different nationalities. Occupations of participants included (N = 1) each in natural sciences, healthcare, and crafts; (N = 2) each in law and administration; (N = 3) each in management and social work; (N = 5) in services; (N = 20) in other professions; and (N = 42) in engineering. Twenty-five participants reported having foot conditions, with sixteen of these in the past and nine currently. In total, 14 had chronic issues and eleven had acute conditions. Overall, 21 participants reported wearing orthopedic aids, including insoles (N = 11), bandages (N = 5), high-leg orthoses (N = 4), and short-leg orthoses (N = 1). In response to the question of whether the participants had previously heard of the term "smart orthoses", 51 responded "no", and 29 responded "yes". Twenty-nine participants were aware of generative AI image generation, twenty-eight had actively used it, and twenty-three had no prior knowledge of the technology.

To investigate whether participant demographics influenced the results, we conducted an ART ANOVA, which showed no statistically significant main or interaction effects of gender, prior AI knowledge, or past orthopedic conditions on SCM, WEAR, and Likert scores (all $p > 0.05$). These results show that demographic factors did not systematically influence the ratings of the participants.

4.1.2. Quantitative Results

Correlation of SCM and WEAR Ratings

A Pearson correlation analysis was conducted to assess the relationship between SCM (means of warm and competence data) and WEAR ratings. A statistically significant moderate positive correlation was found between the Euclidean length of the warmth–competence vector and the WEAR scores, $r(958) = 0.453$, $p < 0.001$, with a 95% confidence interval of (0.402, 0.502). This result confirms the findings from Schwind and Henze [71] that social acceptance ratings correlate with combined competence and warmth data.

Stereotype Content Model (SCM)

The Shapiro–Wilk normality test indicated no normal distribution (only selected SCM competence data showed $p \succeq 0.05$, while all other stimuli for SCM competence and warmth had $p < 0.05$). Therefore, a non-parametric two-factorial ART RM-ANOVA was conducted to determine the effects of Design Type and Orthotic Category on SCM competence and warmth.

For the SCM competence data, statistically significant main effects were found for the Orthotic Category, $F(3, 869) = 56.752$, $p < 0.001$, $\eta_p^2 = 0.464$ (large effect size), and Design Type, $F(2, 869) = 9.931$, $p < 0.001$, $\eta_p^2 = 0.092$ (medium effect size). However, no interaction effect was found between Orthotic Category × Design Type, $F(6, 869) = 1.038$, $p = 0.399$, $\eta_p^2 = 0.031$ (small effect size).

For the SCM warmth data, statistically significant main effects were identified for the Orthotic Category, $F(3, 869) = 3.201$, $p = 0.023$, $\eta_p^2 = 0.278$, and Design Type, $F(2, 869) = 4.493$, $p = 0.012$, $\eta_p^2 = 0.265$, both with large effect sizes. However, the interaction effect of the Orthotic Category × Design Type was not significant, with $F(6, 869) = 1.055$, $p = 0.388$, and $\eta_p^2 = 0.202$ (large effect size).

Post hoc comparisons using Wilcoxon signed-rank tests with Bonferroni correction revealed significant effects in SCM competence and warmth data, as documented in Table 1. Figure 4 displays the mean values of perceived warmth and competence for each of the three Design Types within each of the four Orthotic Categories. Additionally, the figure also presents a comparison across the four ORTHOTIC CATEGORIES within the SCM model to highlight differences in the stereotypical perceptions of these devices.

Table 1. Pairwise comparisons of SCM competence and warmth ratings within orthotic categories and design types. Significance codes: * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$), **** ($p < 0.0001$), ns = not significant.

			SCM Competence				SCM Warmth			
Pairwise Comparisons	**n1**	**n2**	***Stat.***	p	$p_{adj.}$	***Sig.***	***Stat.***	p	$p_{adj.}$	***Sig.***
Short-Leg Orthoses—High-Leg Orthoses	240	240	10094	0.057	0.343	ns	6820	0.612	1	ns
Short-Leg Orthoses—Bandages/Textiles	240	240	2997	<0.001	<0.001	****	5401	0.005	0.03	*
Short-Leg Orthoses—Foot Drop Orthoses	240	240	5367	<0.001	<0.001	****	6286	0.993	1	ns
High-Leg Orthoses—Bandages/Textiles	240	240	2846	<0.001	<0.001	****	5724	0.002	0.013	*
High-Leg Orthoses—Foot Drop Orthoses	240	240	4640	<0.001	<0.001	****	5904	0.360	1	ns
Bandages/Textiles—Foot Drop Orthoses	240	240	11938	<0.001	<0.001	****	7802	0.044	0.265	ns
Generative AI—Development	320	320	22421	<0.001	<0.001	****	15445	<0.001	<0.001	***
Generative AI—Orthopedic products	320	320	21927	<0.001	<0.001	****	13268	0.191	0.573	ns
Development—Orthopedic products	320	320	16596	0.928	1	ns	9968	0.003	0.008	**

Figure 4. SCM ratings of perceived competence (x-axis) and warmth (y-axis) for each of the four ORTHOTIC CATEGORIES. In the upper row, the four quadrants are assigned as follows, from left to right: (**a**) *Short-Leg Orthoses*, (**b**) *High-Leg Orthoses*, (**c**) *Foot Bandages/Textiles*, and (**d**) *Foot Drop Orthoses*. The mean values for the three DESIGN TYPES are shown in separate colors: red (*Generative AI*), blue (*Orthopedic products*), and yellow (*Development concepts*). The lower quadrant (**e**) contains the SCM mean values for each ORTHOTIC CATEGORY: *Short-Leg Orthoses* (purple), *High-Leg Orthoses* (orange), *Foot Bandages/Textiles* (brown), and *Foot Drop Orthoses* (green). The rectangles represent the 95% confidence interval.

Wearable Acceptability Range (WEAR)

The Shapiro–Wilk test for normality indicated that the data are not normally distributed ($p = 0.003$). An ART RM-ANOVA showed statistically significant main effects for the ORTHOTIC CATEGORY, $F(3, 869) = 39.949$, $p < 0.001$, $\eta_p^2 = 0.423$ (large effect size), and DESIGN TYPE, $F(2, 869) = 17.677$, $p < 0.001$, $\eta_p^2 = 0.178$ (large effect size), but no interaction effect for ORTHOTIC CATEGORY × DESIGN TYPE, $F(6, 869) = 1.372$, $p = 0.223$, $\eta_p^2 = 0.048$ (small effect size).

Bonferroni corrected pairwise comparisons were conducted using Wilcoxon signed-rank tests and revealed significant effects between *Generative AI* × *Development concepts* ($p_{\text{adj.}} < 0.001$), *Generative AI* × *Orthopedic products* ($p_{\text{adj.}} < 0.001$), and *Development concepts* × *Orthopedic products* ($p_{\text{adj.}} = 0.021$). Furthermore, pairwise comparisons between ORTHOTIC CATEGORIES revealed five significant effects, which are summarized in Figure 5.

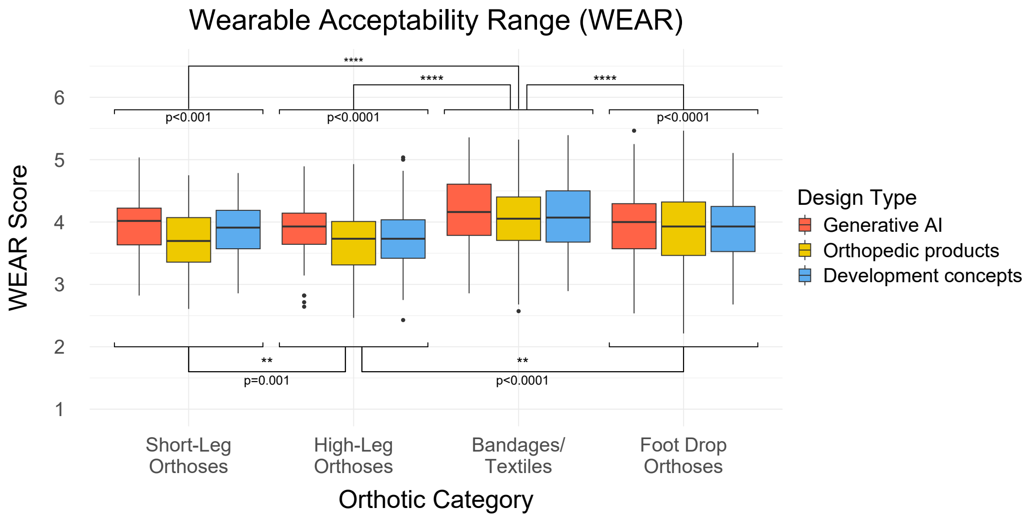


Figure 5. This graph shows the results of the WEAR ratings. The four categories are listed on the x-axis: *short-leg orthoses*, *high-leg orthoses*, *foot supports/textiles* and *foot drop orthoses*, and the y-axis represents the corresponding scores on the WEAR scale. The boxplots are color-coded to differentiate the design types: *Generative AI* in red, *Orthopedic products* in yellow, and *Development concepts* in blue. Asterisks indicate significance levels: * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$), **** ($p < 0.0001$).

Seven-Point Likert Scale

The evaluations of the two statements regarding device acceptance and aesthetic design expectations were not normally distributed ($p < 0.05$).

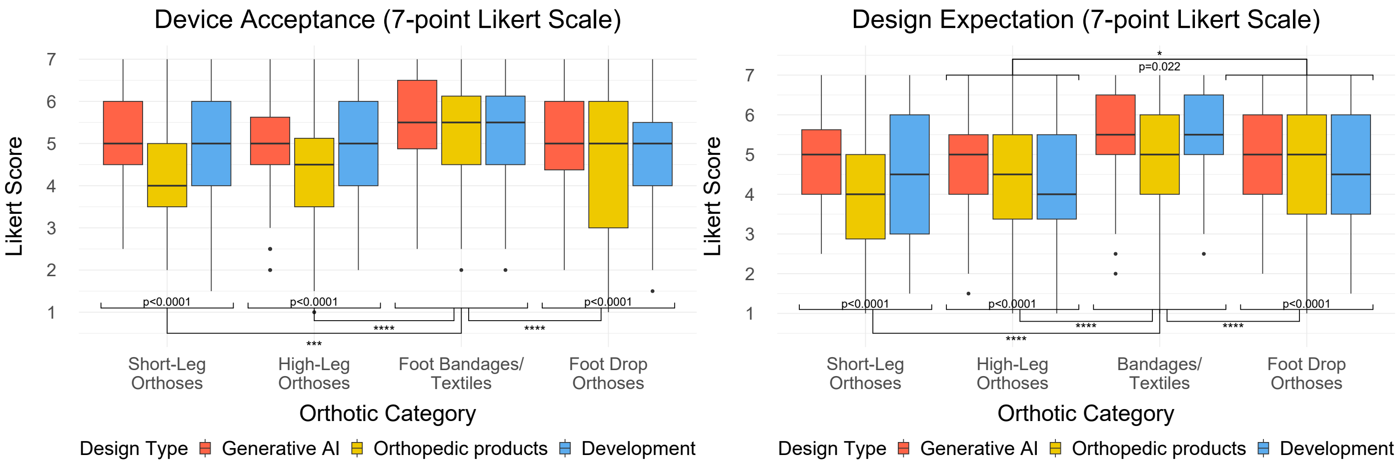
A non-parametric two-factorial ART-ANOVA on rated device acceptance statements revealed a significant main effect for the ORTHOTIC CATEGORY, $F(3, 869) = 24.717$, $p < 0.001$, $\eta_p^2 = 0.336$, and DESIGN TYPE, $F(2, 869) = 24.077$, $p < 0.001$, $\eta_p^2 = 0.247$, as well as a significant interaction effect for ORTHOTIC CATEGORY × DESIGN TYPE, $F(6, 869) = 4.068$, $p < 0.001$, $\eta_p^2 = 0.142$ (each with a large effect size).

Furthermore, the two-factorial ART-ANOVA on rated aesthetic design expectations showed a significant main effect for the ORTHOTIC CATEGORY, $F(3, 869) = 43.730$, $p < 0.001$, $\eta_p^2 = 0.407$, and DESIGN TYPE, $F(2, 869) = 21.613$, $p < 0.001$, $\eta_p^2 = 0.185$ (both with large effect size), as well as a significant interaction effect for ORTHOTIC CATEGORY × DESIGN TYPE, $F(6, 869) = 32.743$, $p = 0.012$, and $\eta_p^2 = 0.079$ (medium effect size).

Pairwise comparisons using Bonferroni-corrected Wilcoxon signed-rank tests revealed statistically significant differences within ORTHOTIC CATEGORIES and DESIGN TYPES, as documented in Table 2. The results of the Likert scale evaluations are displayed in Figure 6.

Table 2. Post hoc pairwise comparisons within orthotic categories and design types for Likert scores of device acceptance and design expectations. Significance codes: * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$), **** ($p < 0.0001$), ns = not significant.

			Device Acceptance				Design Expectation			
Pairwise Comparisons	**n1**	**n2**	***Stat.***	***p***	$p_{adj.}$	***Sig.***	***Stat.***	***p***	$p_{adj.}$	***Sig.***
Short-Leg Orth.—High-Leg Orth.	240	240	7901	0.148	0.888	ns	7804	0.771	1	ns
Short-Leg Orth.—Bandages/Textiles	240	240	4630	<0.001	<0.001	****	2854	<0.001	<0.001	****
Short-Leg Orth.—Foot Drop Orth.	240	240	7456	0.568	1	ns	7370	0.024	0.143	ns
High-Leg Orth.—Bandages/Textiles	240	240	3583	<0.001	<0.001	****	3426	<0.001	<0.001	****
High-Leg Orth.—Foot Drop Orth.	240	240	7032	0.712	1	ns	5688	0.004	0.022	*
Bandages/Textiles—Foot Drop Orth.	240	240	11454	<0.001	<0.001	****	13938	<0.001	<0.001	****
Generative AI—Development	320	320	21972	<0.001	<0.001	****	24376	<0.001	<0.001	****
Generative AI—Orthopedic products	320	320	13612	0.237	0.711	ns	19850	<0.001	<0.001	****
Development—Orthopedic products	320	320	7405	< 0.001	< 0.001	****	12490	0.004	0.011	*



(**a**) (**b**)

Figure 6. This figure contains two boxplot diagrams, including the rated device acceptance (**a**) and aesthetic design expectation (**b**) for the three Design Types in each Orthotic Category. The x-axis lists the four categories: *Short-Leg Orthoses*, *High-Leg Orthoses*, *Foot Bandages/Textiles*, and *Foot Drop Orthoses*. The y-axis represents the corresponding scores from the Likert rating. The boxplots are color-coded to distinguish the design types: *Generative AI* in red, *Orthopedic products* in yellow, and *Development concepts* in blue. Asterisks indicate significance levels: * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$), **** ($p < 0.0001$).

4.1.3. Qualitative Feedback

The axial coding procedure within inductive thematic analysis revealed three main themes: *Aesthetic Design*, *Technical Properties*, and *Usability and Comfort*. Each theme includes both positive and negative perspectives and reflects participant feedback in four Orthotic Categories and three Design Types.

Overall, perceptions of all four Orthotic Categories vary strongly concerning design, technical aspects, usability, and comfort. In general, the Orthotic Categories of *Short-Leg Orthoses* and *High-Leg Orthoses* are often associated with serious injuries. *Short-Leg Orthoses* focus on “stabilization” (P83, P56) and “facilitates mobility for users with lower leg injuries” (P110) but offer limited practicality in daily life. *High-Leg Orthoses* offer “robust protection for serious injuries” (P27, P101, P110), but are “bulky” (P5, P24, P26, P81, P163), “heavy” (P7, P22, P32, P119) and “restrictive” (P39, P83, P113), so their design “looks like a ski boot" (P144). Participants mentioned that these designs "could not be worn with regular shoes" (P75), "leading to clothing restrictions" (P101). In contrast, *Foot Bandages/Textiles* are perceived as "sporty" (P26, P39), "modern" (P34, P156), and "simple" (P56, P84) because of their "unobtrusive design" (P8) and "can be worn with shoes" (P13, P46), but they are also viewed as less suitable for serious injuries. Lastly, *Foot Drop Orthoses* have a "functional design" (P161) which is "not conspicuous" (P56, P84, P163) and directly addresses medical needs but is also seen as "too mechanical" (P8, P156), "not stable" (P21, P53, P73), and "old-fashioned" (P13, P22).

Aesthetic Design: The aesthetic perception varies considerably across the three DESIGN TYPES. The designs of *Generative AI* were perceived as "simple and unobtrusive" (P26, P56, P66), with "subtle colors" (P43, P81), a "clean" (P156) and "modern design [that] could be accepted as a replacement for shoes" (P75), which in some cases appear "futuristic" (P66). However, some participants mentioned that the designs look "too technical" (P63) because "the box looks too extreme" (P156). *Orthopedic products* were associated with a "minimalistic" (P63, P142) and "classic design" (P8, P26), characterized by "neutral colors" (P81) that "looks like a conventional product" (P162). However, these designs were criticized for being visually "unesthetic" (P16, P56, P63)—described as "old-fashioned" (P13), "unfashionable" (P161), "crude" (P107), "strange" (P13, P39), and "too big" (P32, P66)—and therefore perceived as "less socially acceptable" (P16) because of their "robotic appearance" (P32, P119, P144). The medical appearance of some orthoses could affect the wearer's self-confidence because the "impairment attracts attention" (P43). The *Development concepts* were generally recognized as "innovative" (P75), "stylish" (P144), "futuristic" (P13, P34, P60, P64, P156), and "it is nice that the color is different from other design" (P130), which makes them appear "like a fashion item" (P13) and "do not look like a medical product" (P22). In contrast, the bright color was also perceived negatively, along with the "cheap-looking quality" (P63, P66, P72) and "ugly holes" (P84). Additionally, some designs were criticized for their overly "mechanical appearance" (P8, P156) and the "excessive size of the box" (P63), which could lead to "aesthetic acceptance issues" (P24).

Technical Properties: The technical properties of *Generative AI* designs were recognized for "technology integration" (P152) as an "electronic device" (P119). However, some of these technical functions were also negatively considered for their "complexity and the need for regular maintenance or charging" (P152). *Orthopedic products* are recognized for "longevity and low-maintenance" (P109), which "provides strong support and stability for the foot and ankle" (P120) because they "immobilize the ankle and foot" (P27), making them reliable for medical use and effective in the rehabilitation of severe injuries. Although the *Development concepts* featured "lighter" (P22, P25) and "simpler designs" (P5, P161) for "improved mobility" (P110), they were "not stable" (P53, P160) enough to support more serious medical needs. Participants expressed concerns about "durability under heavy loads" (P110), "lack of strength/stiffness" (P101), and the technical efficiency of these designs.

Usability and Comfort: The usability and comfort of the three DESIGN TYPES resulted in contrary user reactions, revealing strengths and weaknesses in product design. *Generative AI* designs faced criticism for certain elements, such as "visible toes" (P39, P72), and raised concerns about "the longevity of materials ... [because the] material could wear out more quickly" (P152). Despite the technical advantages of the *Orthopedic products*, they "can be bulky" (P141) "which can be uncomfortable during everyday activities" (P152), and can reduce comfort over time because it "restricts freedom of movement" (P101). Although some models are described as "comfortable" (P142, P162), there is criticism due to insufficient air circulation because the "feet could sweat" (P84) which can lead to "moisture and skin irritation" (P113). In contrast, it was noted that *Development concepts* are "easy to wear" (P164) and "suitable for everyday use" (P22), offering a practical and "less intrusive" (P8, P161) alternative. However, participants also mentioned that it "can be uncomfortable during long-term use" (P110).

4.2. Study 2

The study group characteristics are described in the Section 4.2.1. The quantitative analysis is documented in Section 4.2.2, including the Correlation of SCM and WEAR Ratings, Stereotype Content Model (SCM) ratings, Wearable Acceptability Range (WEAR) data, and the analysis of the two Seven-Point Likert Scale ratings. The thematic analysis of the qualitative responses is presented in Section 4.2.3.

4.2.1. Participants

In total, 54 out of 133 participants (27 female, 26 male, and 1 diverse) completed the survey and were included in the data analysis. The age of the participants ranged from 18 to 49 years (*M* = 23.30, *SD* = 5.02). The participants had different educational backgrounds and came from nine countries. The participants' occupations varied from (N = 1) in healthcare; (N = 2) each in other services and natural sciences; (N = 3) each in administration, social services, and management; (N = 5) in law; (N = 16) inother professions; and (N = 19) in engineering. Twenty-six participants reported having foot conditions; twenty had conditions in the past and six have current conditions. Of these, 17 were acute diseases and nine were chronic conditions. Eight of them used insoles, seven used bandages, three used a low-leg orthosis, two used a plaster cast, two used a low-leg orthosis, and one used a high-leg orthosis. A total of 20 have already used image-generative AI, 19 participants have no experience with such tools, and 15 are only familiar with the tools from hearsay.

Similarly to our first study, we conducted an ART ANOVA to examine the influence of demographic factors. The results showed no statistically significant main or interaction effects on SCM, WEAR, and Likert scores (all $p > 0.05$), indicating that demographic variables did not influence participant ratings.

4.2.2. Quantitative Results

Correlation of SCM and WEAR Ratings

The Pearson correlation analysis showed a statistically significant correlation between the Euclidean length of the SCM warmth-competence vector (means of warm and competence data) and the WEAR scores: $r(430) = 0.800$, $p < 0.001$, with a 95% confidence interval of (0.763, 0.831).

Stereotype Content Model (SCM)

The Shapiro–Wilk normality test indicated a significant deviation from normality for SCM competence and warmth (both $p < 0.0001$). A non-parametric two-factorial ART RM-ANOVA for the SCM competence data showed a statistically significant main effect for GPT, $F(1, 371) = 124.871$, $p < 0.0001$, $\eta_p^2 = 0.448$, and for KEYWORD, $F(3, 371) = 8.499$, $p < 0.0001$, $\eta_p^2 = 0.142$ (both with large effect size). However, no significant interaction effect was found for GPT × KEYWORD, $F(3, 371) = 1.198$, $p = 0.310$, $\eta_p^2 = 0.023$ (small effect size). For the SCM warmth data, a significant main effect was identified for GPT, $F(1, 371) = 62.461$, $p < 0.0001$, and $\eta_p^2 = 0.471$ (large effect size). However, no significant effect was found for KEYWORD, $F(3, 371) = 1.282$, $p = 0.280$, $\eta_p^2 = 0.052$, nor for the interaction effect of GPT × KEYWORD, $F(3, 371) = 1.267$, $p = 0.285$, $\eta_p^2 = 0.051$ (both with a small effect size). Post hoc comparisons using Wilcoxon signed-rank tests with Bonferroni correction revealed significant effects in SCM competence and warmth data, as documented in Table 3. The mean values of perceived warmth and competence are depicted in Figure 7.

Table 3. Pairwise comparisons of SCM competence and warmth ratings within keywords and GPTs. Significance codes: * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$), **** ($p < 0.0001$), ns = not significant.

			SCM Competence				SCM Warmth			
Pairwise Comparisons	**n1**	**n2**	***Stat.***	p	$p_{adj.}$	***Sig.***	***Stat.***	p	$p_{adj.}$	***Sig.***
No Keyword—Usability	108	108	1482	0.312	1	ns	868	0.337	1	ns
No Keyword—Social Acceptability	108	108	1943	0.482	1	ns	1331	0.605	1	ns
No Keyword—Sporty Design	108	108	748	<0.001	<0.001	****	850	0.146	0.876	ns
Usability—Social Acceptability	108	108	2135	0.075	0.450	ns	1508	0.186	1	ns
Usability—Sporty Design	108	108	725	<0.001	<0.001	****	914	0.221	1	ns
Social Acceptability—Sporty Design	108	108	764	<0.001	<0.001	****	854	0.107	0.642	ns
No Keyword: ChatGPT—Orth.FootGPT	54	54	942	0.002	0.002	**	1135	0.046	0.046	*
Usability: ChatGPT—OrthoticFootGPT	54	54	828	<0.001	<0.001	***	994	0.004	0.004	**
Social Accept.: ChatGPT—Orth.GPT	54	54	777	<0.001	<0.001	****	875	<0.001	<0.001	***
Sporty Design: ChatGPT—Orth.FootGPT	54	54	830	<0.001	<0.001	***	1069	0.016	0.016	*

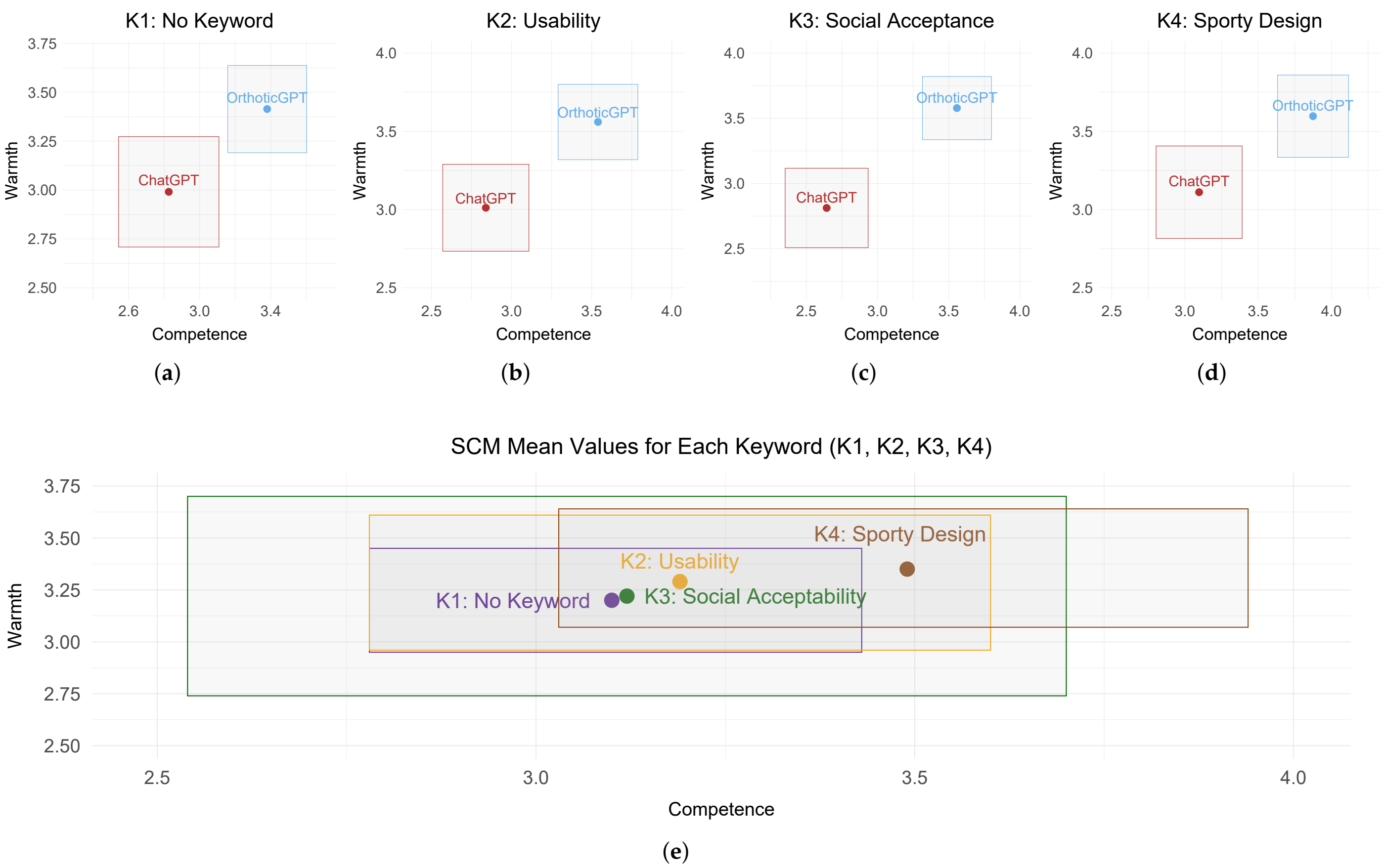


Figure 7. SCM ratings of perceived competence (x-axis) and warmth (y-axis) for each of the four KEYWORDS. In the upper row, the four quadrants are assigned as follows, from left to right: (**a**) *No Keyword*, (**b**) *Usability*, (**c**) *Social Acceptability*, and (**d**) *Sporty Design*. The mean values for two GPTs are shown in separate colors: red (*ChatGPT*) and blue (*OrthoticFootGPT*). The lower quadrant (**e**) contains the SCM mean values for each KEYWORD: *No Keyword* (purple), *Usability* (orange), *Social Acceptability* (green), and *Sporty Design* (brown). The rectangles represent the 95% confidence interval.

Wearable Acceptability Range (WEAR)

The Shapiro–Wilk normality test indicated that the data is not normally distributed ($p < 0.0001$). An ART RM-ANOVA showed statistically significant main effects for the GPT, $F(1, 371) = 109.325$, $p < 0.0001$, $\eta_p^2 = 0.450$ (large effect size), and for KEYWORD,

$F(3, 371) = 6.270$, $p = 0.0003$, $\eta_p^2 = 0.123$ (medium effect size). However, no interaction effect was found for GPT × KEYWORD, $F(3, 371) = 1.948$, $p = 0.121$, and $\eta_p^2 = 0.042$ (small effect size).

Bonferroni-corrected pairwise comparisons were conducted using Wilcoxon signed-rank tests, which revealed statistically significant differences between *No Keyword* × *Sporty Design* ($p_{adj} < 0.0001$), *Usability* × *Sporty Design* ($p_{adj} = 0.0002$), and *Social Acceptability* × *Sporty Design* ($p_{adj} < 0.0001$). The pairwise comparison between *ChatGPT* and *OrthoticFootGPT* was statistically significant, with $p < 0.0001$. Pairwise comparisons between the GPT and KEYWORD demonstrated statistically significant differences across all keywords: *No Keywords* ($p_{adj.} = 0.0004$), *Usability* ($p_{adj.} = 0.0002$), *Social Acceptability* ($p_{adj.} < 0.0001$), and *Sporty Design* ($p_{adj.} = 0.009$). The results of the WEAR scale are summarized in Figure 8.

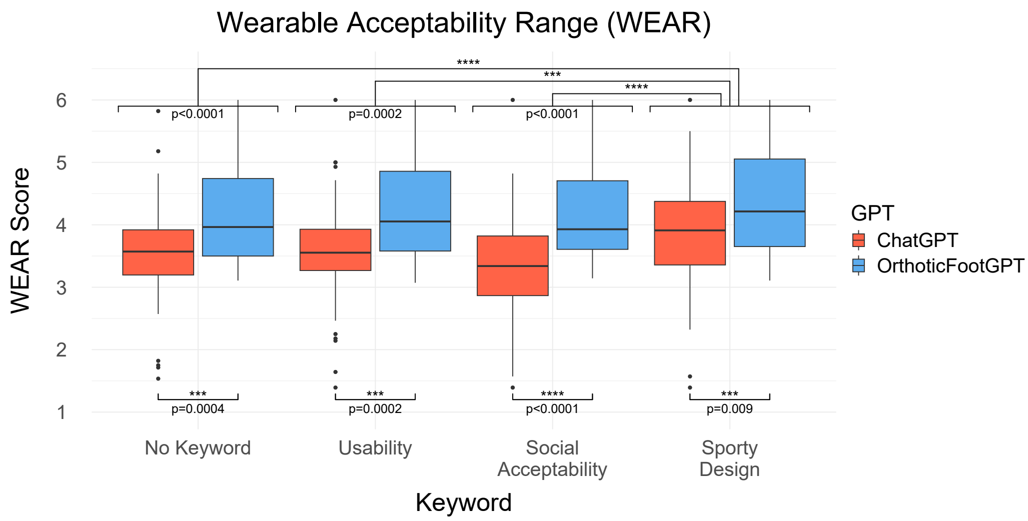


Figure 8. This graph shows the results of the WEAR ratings. The four Keywords are listed on the x-axis, *No Keyword*, *Usability*, *Social Acceptability*, and *Sporty Design*, and the y-axis represents the corresponding scores on the WEAR scale. The boxplots are color-coded to distinguish the GPT: *ChatGPT* in red and *OrthoticFootGPT* in blue. Asterisks indicate significance levels: * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$), **** ($p < 0.0001$).

Seven-Point Likert Scale

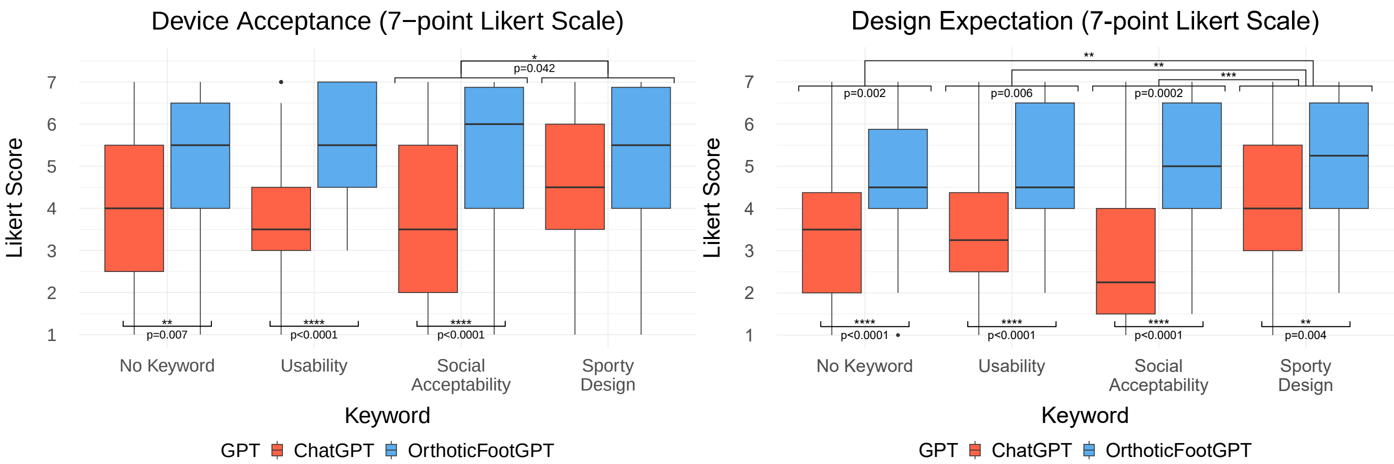
The Shapiro–Wilk normality test for the two statements on device acceptance and aesthetic design expectations indicated no normal distribution ($p < 0.0001$).

A non-parametric two-factorial ART-ANOVA on rated device acceptance statements revealed a significant main effect for the GPT, $F(1, 371) = 90.864$, $p < 0.0001$, $\eta_p^2 = 0.442$ (large effect size), and for KEYWORD, $F(3, 371) = 3.081$, $p = 0.027$, $\eta_p^2 = 0.074$ (medium effect size), as well as an interaction effect for GPT × KEYWORD, $F(3, 371) = 4.834$, $p = 0.002$, and $\eta_p^2 = 0.111$ (medium effect size).

The two-factorial ART-ANOVA on rated aesthetic design expectations showed a significant main effect for GPT, $F(1, 371) = 129.196$, $p < 0.0001$, $\eta_p^2 = 0.442$, and KEYWORD, $F(3, 371) = 7.397$, $p < 0.0001$, $\eta_p^2 = 0.119$ (both with a large effect size), as well as a significant interaction effect for GPT × KEYWORD, $F(3, 371) = 4.021$, $p = 0.007$, and $\eta_p^2 = 0.068$ (medium effect size). Post hoc pairwise comparisons using the Wilcoxon signed-rank test with Bonferroni correction revealed statistically significant differences and notable trends in both device acceptance and design expectation data, as documented in Table 4. The results are presented in Figure 9.

Table 4. Post hoc pairwise comparisons within keywords and GPTs for Likert scores of device acceptance and design expectation. Significance codes: * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$), **** ($p < 0.0001$), ns = not significant.

			Device Acceptance				Design Expectation			
Pairwise Comparisons	**n1**	**n2**	***Stat.***	***p***	$p_{adj.}$	***Sig.***	***Stat.***	***p***	$p_{adj.}$	***Sig.***
No Keyword—Usability	108	108	1382	0.548	1	ns	1545	0.282	1	ns
No Keyword—Social Acceptability	108	108	1382	0.199	1	ns	1833	0.304	1	ns
No Keyword—Sporty Design	108	108	1110	0.066	0.398	ns	1093	<0.001	0.002	**
Usability—Social Acceptability	108	108	1529	0.325	1	ns	2022	0.030	0.179	ns
Usability—Sporty Design	108	108	732	0.011	0.064	ns	934	<0.001	0.006	**
Social Acceptability—Sporty Design	108	108	1030	0.007	0.042	*	836	<0.001	<0.001	***
No Keyword: ChatGPT—Orth.FootGPT	54	54	1022	0.007	0.007	**	819	<0.001	<0.001	****
Usability: ChatGPT—OrthoticFootGPT	54	54	692	<0.001	<0.001	****	712	<0.001	<0.001	****
Social Accept.: ChatGPT—Orth.GPT	54	54	744	<0.001	<0.001	****	540	<0.001	<0.001	****
Sporty Design: ChatGPT—Orth.FootGPT	54	54	1212	0.129	0.129	ns	997	0.004	0.004	**



(**a**) (**b**)

Figure 9. This figure contains two boxplot diagrams, including the rated device acceptance (**a**) and aesthetic design expectation (**b**) for the four KEYWORDS in each GPT. The x-axis lists the four Keywords: *No Keyword*, *Usability*, *Social Acceptability*, and *Sporty Design*. The y-axis represents the corresponding scores from the Likert rating. The boxplots are color-coded to distinguish the GPT: *ChatGPT* in red and *OrthoticFootGPT* in blue. Asterisks indicate significance levels: * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$), **** ($p < 0.0001$).

4.2.3. Qualitative Feedback

An inductive thematic analysis on transcribed data revealed three main themes: *Aesthetic Design*, *Functionality*, as well as *Comfort and Fit*. These three themes include both positive and negative perspectives and reflect the participants' feedback on the two GPTs and four KEYWORDS.

Aesthetic Design: The designs with *No Keyword* were generally described as "standard" (P141), "simple" (P56), and "not visually appealing" (P61) when generated by *ChatGPT*. In contrast, designs generated by *OrthoticFootGPT* were characterized as "modern" (P83, P90), "aesthetic" (P9), and "compact" (P60), with a "positive shape and design" (P74) resembling a "mixture of a boot and a sports shoe" (P102). For the keyword *Usability*, *ChatGPT* designs were recognized as "similar to shoes" (P33) with a "good color" (P14) but were also criticized for being "old-fashioned" (P21) and "unaesthetic" (P61). Meanwhile, *OrthoticFootGPT* designs were praised as "aesthetic" (P56), "modern and sporty"

(P21), and also "similar to shoes" (P41, P69). Furthermore, one participant stated that "the eye-catching design ensures that the orthosis is easily recognized by others, which can lead to more consideration from others" (P108). Images generated using the keyword *Social Acceptability* via *ChatGPT* were described as "minimalistic" (P24) with a "positive color" (P14), but their perception was negatively impacted by a "dubious shape" (P21) and "incomprehensible design" (P47). On the other hand, designs from *OrthoticFootGPT* were regarded as "very aesthetic and modern" (P41), "sporty" (P24), and featuring a "nice design" (P83), due to "less conspicuous Velcro fasteners" (P90) and a resemblance to "winter boots" (P159). In general, the *Sporty Design* keyword led to designs perceived as modern and sporty, which were positively received by participants. The *ChatGPT* outputs were described as a "nice and modern design" (P24) contributing to a "self-confident appearance" (P74). In comparison, *OrthoticFootGPT* designs were associated with a "sporty design" (P9), resembling "sport shoes" (P74, P102, P138) and perceived as designs that "remind one of a fashion brand" (P89). It was also positively noted that "the toes are not visible" (P94).

Functionality: The use of *No Keyword* with *ChatGPT* raised concerns about functionality, as the designs were perceived as "not effective" (P157) and "not stable" (P90, P150) due to the "missing insole" (P9, P14) and because they "offer less protection (e.g., no padding)" (P36). In contrast, the *OrthoticFootGPT* designs "offer good stability and fulfill [their] functional requirements effectively" (P61) because they are "easy to attach and remove" (P89, P90, P152). For the keyword *Usability*, *ChatGPT* designs were criticized for being "too mechanical" (P150) and "complicated to use" (P105, P111, P149). Meanwhile, *OrthoticFootGPT* outputs were associated with "simple handling" (P36, P56), due to "a good balance of stability and comfort" (P36) and because "it also gives the feeling that it has very useful functions" (P21). In the context of *Social Acceptability*, *ChatGPT* designs were described as "too bulky, seems heavy" (P14), "unrealistic" (P60), and "impractical" (P37), primarily due to "too many straps" (P9, P89) and "components are mainly made of textile. Water . . . can be absorbed" (P79). In contrast, *OrthoticFootGPT* designs were perceived as "very innovative" (P93), featuring "a good sole, similar to a shoe" (P14), making them an "eye-catcher for everyone" (P21). Regarding *Sporty Design*, *ChatGPT* was noted for its "functional and rather simple design . . . suitable for a broad target group" (P90). Similarly, *OrthoticFootGPT* designs were defined as "robust" (P94), "stable" (P36, P105), and "breathable" (P33), with functionality that is "easy to integrate for sports activities" (P89).

Comfort and Fit: The primary issues with *ChatGPT* designs using *No Keyword* were identified as being "uncomfortable" (P21) and "impractical due to open toes" (P37), concerns that were similarly reflected in the keywords *Usability* and *Social Acceptability*. In contrast, the *OrthoticFootGPT* designs with *No Keyword* were perceived more positively, as "the orthosis is easily adjustable and can be customized" (P61) and it "has good padding on the foot" (P36). For the keyword *Usability*, the *OrthoticFootGPT* was highlighted for being "easy to use" (P36) and it "is light and comfortable to wear, even for long periods" (P61), which could be "suitable for thicker calves" (P74). In the context of *Social Acceptability*, designs generated by *OrthoticFootGPT* were described as resembling a "sport shoe" (P21) or "winter boots" (P159), with positive feedback emphasizing that "no toes are visible" (P94). Regarding *Sporty Design*, a participant described the *ChatGPT* output as follows: "It looks like a boot. It does not attract attention and is therefore great for everyday wear. It makes you feel more confident" (P74). Meanwhile, the *OrthoticFootGPT* designs were seen as both "comfortable" (P157) and "sporty" (P47, P60, P92, P101, P117), and they "look like an orthopedic hiking/running/football shoe" (P157) which is "great for social integration" (P74). Furthermore, one participant noted that "the orthosis appears to be easy to put on with the fasteners, which could potentially make everyday life easier for the wearer", but also mentioned negatively that "the unobtrusive design could lead to people taking less notice of the wearer" (P108).

5. Discussion

5.1. The Impact of AI-Generated and Conventional Orthotic Designs Across Device Categories on Social Acceptability

In our first study, we conducted a mixed-method online survey to explore the impact of three DESIGN TYPES and four ORTHOTIC CATEGORIES on social acceptance. The quantitative analyses of Likert scales, as well as the SCM and WEAR models, indicated that ORTHOTIC CATEGORIES such as *Foot Bandages/Textiles* achieved significantly higher acceptance ratings, followed by *Foot Drop Orthoses* and then *Short-Leg* and *High-Leg Orthoses*. Furthermore, the *Generative AI* DESIGN TYPE had a significant impact on perceived acceptability, as these devices were associated with stereotypes of greater competence and warmth compared to medical or developmental designs, which confirms our hypothesis. These findings were supported by the qualitative feedback, which highlighted the potential of using *Generative AI* to consider user preferences and increase acceptance of orthopedic footwear.

Overall, these results confirm the potential of integrating AI into the design process for wearable foot devices. However, the significantly lower acceptance rates for short and high-leg orthoses represent a consistent challenge that reflects the concerns reported in previous research. By identifying the challenges of user acceptance associated with different categories of orthoses, this study contributes to a deeper understanding of the factors that influence the social acceptance of orthotic devices. Our findings are valuable for future developments aimed at enhancing the aesthetic design of these devices to better meet user needs.

5.2. The Impact of GPT Customization and Prompt Keywords on the Social Acceptability of AI-Generated Orthotic Designs

The second study examined the impact of high-leg orthosis designs generated using *OrthoticFootGPT* and *ChatGPT*, as well as the influence of four different prompt structures incorporating specific keywords on social acceptability. This extends the results of the first study to explore if a personalized GPT and specific KEYWORDS can have a systematic positive influence on user perception. The quantitative results indicate that the customized *OrthoticFootGPT* model can enhance acceptance ratings compared to *ChatGPT*. Additionally, the study showed that different keywords evoke different stereotypical perceptions of the wearable device. In particular, the keyword *Sporty Design* led to significantly better ratings compared to other keyword variations, suggesting that aesthetic framing plays a crucial role in user perception. These findings are consistent with the qualitative feedback, which revealed a discrepancy between the perception of medical orthoses and more socially integrated designs, such as those inspired by the aesthetics of footwear or sports. Participants expressed contrasting preferences regarding the visual appearance of orthotic designs: while some preferred an inconspicuous design to avoid attracting attention, others emphasized that a more visible, eye-catching design could facilitate social recognition and consideration by others. This contrast illustrates the complexity of the relationship between aesthetics as well as functional and social expectations.

These results highlight the potential of generative AI to enhance the design process of wearable medical devices. Furthermore, our results align with previous studies on wearable device perception, emphasizing that design plays a crucial role in acceptance [35,36]. In addition, these results support earlier findings that highlight a discrepancy in the literature regarding the stigmatization of medical devices, where functional necessity often conflicts with social acceptability, leading to lower acceptance [36].

Similar to findings by Sehrt et al. [50], who observed that wearables positioned on the ankle received lower social acceptance scores, our study showed that high-leg orthoses face significant acceptance challenges compared to other orthotic device categories. By demonstrating that customized GPT models and prompt engineering can systematically shape social acceptability, our study builds on prior work [22,23] that highlights the importance of structured input in AI-assisted design.

Therefore, we recommend that future developments prioritize the use of customized GPT models in combination with personalized prompting strategies that explicitly address user preferences and social perception factors.

5.3. Implications

The results obtained from the two studies conducted show the potential of generative AI to improve the social acceptability of foot wearable devices and demonstrate its applicability in product design. Building on existing work, such as the use of DALL-E for designing hand orthoses [30], our study extends this approach to foot orthoses, with a specific focus on social acceptance factors. The integration of image-generative AI in the design phase can significantly improve acceptance and lead to more user-centered orthosis designs. In particular, the consideration of user preferences with prompting alongside the technical functionalities of wearables offers a promising approach for personalization in product development. Furthermore, the findings from this research extend beyond orthopedic footwear, affecting broader applications within the fields of HCI, user experience (UX) design, and the integration of social factors in product development. Understanding how AI-generated designs influence product acceptance offers valuable insights for improving design processes across various applications and product categories. For example, designers can integrate user feedback directly into aesthetic and functional design aspects to enhance user engagement and satisfaction. Moreover, this study highlights the potential of generative AI as a valuable tool for inspiring the design of socially driven consumer products and wearable technology. We recommend the use of customized, fine-tuned GPT models to generate user-specific outputs that align with product specifications. Furthermore, incorporating specific keywords related to functionality, target user groups, and design preferences directly within the prompt can enhance the quality and relevance of the generated results.

Beyond improving social acceptability, AI-generated designs also introduce new opportunities for streamlining the product development process. While traditional design approaches rely entirely on manual modeling, which can be time-consuming and expensive, especially when adapting to individual user preferences, AI-generated designs still require manual expert input in the post-processing phase. This includes converting 2D images into 3D data, adapting the design to specific medical requirements, and preparing the data for manufacturing. Related work has demonstrated that integrating AI into the shoe design process can reduce design time by 59% compared to traditional methods while also lowering production costs [72]. These findings indicate that AI-supported workflows have the potential to increase efficiency in orthotic design while maintaining a high degree of individualization.

5.4. Limitations

Our studies have some limitations that affect the generalizability of the results. Although our studies included participants from various backgrounds, the lack of gender balance in the first study and the inclusion of healthy individuals in both studies could potentially affect the external validity. However, our analysis showed that demographic factors did not systematically influence participants' ratings, which indicates that the observed effects are not due to the sample population. Nevertheless, a more patient-centered focus could provide deeper insights into the specific needs and perceptions of individuals with orthopedic conditions. While some results did not reach statistical significance, they indicate notable trends that suggest potential effects worth further investigation. Furthermore, the results are limited to the specific stimuli and orthotic categories that were used in the study. Additionally, the AI-generated designs, which rely on individual prompts or selected pictures of orthopedic products, cannot be consistently reproduced with identical inputs. This inconsistency requires multiple iterations of prompts to achieve the desired outcomes.

Another notable limitation is that AI-generated designs do not adhere to any medical guidelines or standards, as they are primarily visual concepts rather than functional prototypes. While the prompts and images were adjusted to the medical functions and specific requirements of the selected orthosis categories, DALL-E image generation is not specialized for medical functions and does not take manufacturing constraints or biocompatibility into account. The results are limited to the perspective of end users and do not consider technical aspects that are relevant from an expert perspective, such as material feasibility or regulatory compliance.

The generative AI tool DALL-E was limited to its current version during both studies. Furthermore, biases in the training datasets of AI models could reinforce stereotypes (e.g., related to ethnicity, gender, or other factors) [73]. These factors are critical as they could influence the social acceptance of the designs, particularly if they fail to address the needs and preferences of various user groups or if they misrepresent them. Therefore, any application of such AI-generated designs in real-world medical products must carefully consider and comply with strict regulatory standards to ensure their safety and effectiveness.

5.5. Future Work

The growing field of AI applications will contribute to opening new possibilities for user-centered design solutions. The potential for generating 3D models that are compatible with Computer-Aided Design (CAD) software could significantly enhance the development process, particularly in the area of rapid prototyping. Future developments should focus on training device-specific GPTs to generate tailored image outputs that meet user needs. Moreover, refining and validating prompt structures will be crucial to achieving more personalized results. Furthermore, to better understand the context and impact of AI-generated designs on social acceptability, future research should extend beyond orthopedic footwear to include diverse product categories. This extension would provide a comprehensive overview of how generative AI can influence product acceptance in different fields. By addressing these areas, follow-up work can make an important contribution to the further development of AI in product design and potentially lead to more effective and socially accepted solutions. Follow-up studies should include a more diverse participant sample, focused on individuals with orthopedic conditions, to better understand user-specific requirements. An exemplary case study could demonstrate how AI-generated design can be integrated into a patient-centric design process that covers the entire workflow, including patient requirements, AI-based design generation, post-processing of 3D models, product personalization based on anatomical needs, manufacturing aspects, and product testing. While long-term biocompatibility testing may be required for regulatory approval, initial usability studies can focus on short-term comfort and usability. Additionally, human intervention by expert designers remains essential to test, validate, and refine AI-generated outputs to ensure practical applicability and manufacturability.

To ensure that AI-generated orthotic designs consider different cultural factors, AI models should be trained on datasets that are representative of diverse user demographics. Additionally, engaging patients with orthopedic conditions in co-design sessions can help align AI-generated outputs with real-life needs and prevent the reinforcement of stereotypes in training data. Involving clinicians, orthopedic experts, and diverse patient representatives in the AI design evaluation process ensures that biased or stereotypical outputs are identified and corrected early. Future research must critically evaluate these biases and develop strategies to ensure that AI-assisted design workflows align with ethical principles and medical standards.

6. Conclusions

In this paper, we explored the influence of image-generative AI on the social acceptance of footwear designs through two studies involving 134 participants. Our first study demonstrated that AI-generated designs can significantly enhance perceived user acceptance compared to conventional designs. The second study showed that customizing prompts with specific keywords and using a personalized GPT can better tailor these designs to user preferences and therefore improve acceptance. These findings suggest that integrating image-generative AI with personalized prompting strategies in the design process could transform how these devices are perceived and accepted, aligning product functionality with user expectations more effectively. This approach introduces a new framework for user-centric design processes, leveraging AI-driven systems to adapt designs based on specific user inputs. Our findings are not limited to medical wearables and could be extended to various applications and products. Overall, this study enhances our understanding of how AI-generated outputs impact user perception, setting the groundwork for future research to explore new GPT models and expand these findings across different contexts.

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References

1. Mohaddis, M.; Maqsood, S.A.; Ago, E.; Singh, S.; Naim, Z.; Prasad, S. Enhancing Functional Rehabilitation Through Orthotic Interventions for Foot and Ankle Conditions: A Narrative Review. *Cureus* **2023**, *15*, e49103. [CrossRef]
2. Slater, G.; Slater, T. Current concepts review: Orthotics in post-operative foot and ankle surgery. *J. Regen. Biol. Med.* **2022**, *4*, 1–4. [CrossRef] [PubMed]
3. Surmen, H.K.; Akalan, N.E.; Arslan, Y.Z. Design, manufacture, and selection of ankle-foot-orthoses. In *Advanced Methodologies and Technologies in Artificial Intelligence, Computer Simulation, and Human-Computer Interaction*; IGI Global: Hershey, PA, USA, 2019; pp. 250–266.
4. Leite, M.; Soares, B.; Lopes, V.; Santos, S.; Silva, M.T. Design for personalized medicine in orthotics and prosthetics. *Procedia CIRP* **2019**, *84*, 457–461.
5. Ghoseiri, K.; Bahramian, H. User satisfaction with orthotic and prosthetic devices and services of a single clinic. *Disabil. Rehabil.* **2012**, *34*, 1328–1332.
6. Swinnen, E.; Kerckhofs, E. Compliance of patients wearing an orthotic device or orthopedic shoes: A systematic review. *J. Bodyw. Mov. Ther.* **2015**, *19*, 759–770. [CrossRef]
7. Faux-Nightingale, A.; Kelemen, M.; Stewart, C. Ankle-foot orthosis adherence in children and adolescents with cerebral palsy: A scoping review. *Prosthet. Orthot. Int.* **2022**, *46*, 351–356. [CrossRef] [PubMed]
8. Dabnichki, P.; Pang, T.Y. User-Centered Design Framework for Personalized Ankle–Foot Orthoses. *Prosthesis* **2025**, *7*, 11. [CrossRef]
9. Exterkate, S.H.; Jongebloed-Westra, M.; Ten Klooster, P.M.; Koffijberg, H.; Bode, C.; van Gemert-Pijnen, J.E.; van Baal, J.G.; van Netten, J.J. Objectively assessed long-term wearing patterns and predictors of wearing orthopaedic footwear in people with diabetes at moderate-to-high risk of foot ulceration: A 12 months observational study. *J. Foot Ankle Res.* **2023**, *16*, 60. [CrossRef]
10. Finco, M.G.; Cay, G.; Lee, M.; Garcia, J.; Salazar, E.; Tan, T.W.; Armstrong, D.G.; Najafi, B. Taking a Load Off: User Perceptions of Smart Offloading Walkers for Diabetic Foot Ulcers Using the Technology Acceptance Model. *Sensors* **2023**, *23*, 2768. [CrossRef]
11. Mageshkumar, G.; Prasanna, G.; Sakthi Priya, G.; Samkilbart, A. Design of IoT-Based Orthotic Footwear for Lower Limb Correction and Alignment. In Proceedings of the 2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 14–15 March 2024; Volume 1, pp. 633–638.
12. Imbesi, S.; Scataglini, S. A User Centered Methodology for the Design of Smart Apparel for Older Users. *Sensors* **2021**, *21*, 2804. [CrossRef]
13. Orlando, J.M.; Li, B.; Bodt, B.; Lobo, M.A. Users' perceptions about lower extremity orthotic devices: A systematic review. *Arch. Phys. Med. Rehabil.* **2023**, *104*, 645–655. [CrossRef] [PubMed]
14. van der Wilk, D.; Hijmans, J.M.; Postema, K.; Verkerke, G.J. A user-centered qualitative study on experiences with ankle-foot orthoses and suggestions for improved design. *Prosthet. Orthot. Int.* **2018**, *42*, 121–128. [CrossRef]
15. Adhikari, M.S.; Verma, Y.K.; Sindhwani, M.; Sachdeva, S. Generative AI Tools for Product Design and Engineering. In *Generative Artificial Intelligence in Finance: Large Language Models, Interfaces, and Industry Use Cases to Transform Accounting and Finance Processes*; Wiley: Hoboken, NJ, USA, 2025; pp. 299–325.
16. Suessmuth, J.; Fick, F.; Van Der Vossen, S. Generative AI for Concept Creation in Footwear Design. In *Proceedings of the ACM SIGGRAPH 2023 Talks*; Association for Computing Machinery: New York, NY, USA, 2023. [CrossRef]
17. DALL·E 3. OpenAI. Available online: https://openai.com/index/dall-e-3/ (accessed on 10 January 2025).
18. Alam, M.F.; Lentsch, A.; Yu, N.; Barmack, S.; Kim, S.; Acemoglu, D.; Hart, J.; Johnson, S.; Ahmed, F. From Automation to Augmentation: Redefining Engineering Design and Manufacturing in the Age of NextGen-AI. An MIT Exploration of Generative AI. 2024. Available online: https://mit-genai.pubpub.org/pub/9s6690gd (accessed on 10 February 2025).
19. Edwards, K.M.; Man, B.; Ahmed, F. Sketch2Prototype: Rapid Conceptual Design Exploration and Prototyping with Generative AI. *Proc. Des. Soc.* **2024**, *4*, 1989–1998. [CrossRef]
20. Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A.N.; Kaiser, L.; Polosukhin, I. Attention is all you need. In Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS'17), Red Hook, NY, USA, 4–9 December 2017; pp. 6000–6010.
21. Brisco, R.; Hay, L.; Dhami, S. Exploring the role of text-to-image AI in concept generation. *Proc. Des. Soc.* **2023**, *3*, 1835–1844. [CrossRef]
22. White, J.; Fu, Q.; Hays, S.; Sandborn, M.; Olea, C.; Gilbert, H.; Elnashar, A.; Spencer-Smith, J.; Schmidt, D.C. A prompt pattern catalog to enhance prompt engineering with chatgpt. *arXiv* **2023**, arXiv:2302.11382.
23. Liu, V.; Chilton, L.B. Design Guidelines for Prompt Engineering Text-to-Image Generative Models. In Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22), New Orleans, LA, USA, 29 April–5 May 2022. [CrossRef]

24. Goodfellow, I.; Pouget-Abadie, J.; Mirza, M.; Xu, B.; Warde-Farley, D.; Ozair, S.; Courville, A.; Bengio, Y. Generative adversarial networks. *Commun. ACM* **2020**, *63*, 139–144. [CrossRef]
25. Chiou, L.Y.; Hung, P.K.; Liang, R.H.; Wang, C.T. Designing with AI: An Exploration of Co-Ideation with Image Generators. In Proceedings of the 2023 ACM Designing Interactive Systems Conference (DIS '23), Pittsburgh, PA, USA, 10–14 July 2023; pp. 1941–1954. [CrossRef]
26. Barros, M.; Ai, Q. Designing with words: Exploring the integration of text-to-image models in industrial design. *Digit. Creat.* **2024**, *35*, 378–391. [CrossRef]
27. Lee, Y.H.; Chiu, C.Y. The Impact of AI Text-to-Image Generator on Product Styling Design. In *Proceedings of the Human Interface and the Management of Information*; Mori, H., Asahi, Y., Eds.; Springer: Cham, Switzerland, 2023; pp. 502–515. [CrossRef]
28. Cai, A.; Rick, S.R.; Heyman, J.L.; Zhang, Y.; Filipowicz, A.; Hong, M.; Klenk, M.; Malone, T. DesignAID: Using Generative AI and Semantic Diversity for Design Inspiration. In Proceedings of the ACM Collective Intelligence Conference (CI '23), Delft, The Netherlands, 6–9 November 2023; Association for Computing Machinery: New York, NY, USA, 2023; pp. 1–11. [CrossRef]
29. Elasri, M.; Elharrouss, O.; Al-Maadeed, S.; Tairi, H. Image generation: A review. *Neural Process. Lett.* **2022**, *54*, 4609–4646. [CrossRef]
30. Popescu, D. Exploring the use of ChatGPT and Dall-E for the preliminary design of 3D-printed wrist-hand orthoses. *Proc. Manuf. Syst.* **2023**, *18*, 97–102.
31. Bartlett, K.A.; Camba, J.D. Generative Artificial Intelligence in Product Design Education: Navigating Concerns of Originality and Ethics. *Int. J. Interact. Multimed. Artif. Intell.* **2024**, *8*, 55–64. [CrossRef]
32. Dunne, L.E.; Profita, H.; Zeagler, C.; Clawson, J.; Gilliland, S.; Do, E.Y.L.; Budd, J. The social comfort of wearable technology and gestural interaction. In Proceedings of the 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Chicago, IL, USA, 26–30 August 2014; pp. 4159–4162. [CrossRef]
33. Dunne, L.; Profita, H.; Zeagler, C. Chapter 1.2—Social Aspects of Wearability and Interaction. In *Wearable Sensors*; Sazonov, E., Neuman, M.R., Eds.; Academic Press: Oxford, UK, 2014; pp. 25–43. [CrossRef]
34. Yang, H.; Yu, J.; Zo, H.; Choi, M. User acceptance of wearable devices: An extended perspective of perceived value. *Telemat. Inform.* **2016**, *33*, 256–269. [CrossRef]
35. Profita, H.; Albaghli, R.; Findlater, L.; Jaeger, P.; Kane, S.K. The AT Effect: How Disability Affects the Perceived Social Acceptability of Head-Mounted Display Use. In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16), San Jose, CA, USA, 7–12 May 2016; Association for Computing Machinery: New York, NY, USA, 2016; pp. 4884–4895. [CrossRef]
36. Kelly, N.; Gilbert, S.B. The wearer, the device, and its use: Advances in understanding the social acceptability of wearables. *Proc. Hum. Factors Ergon. Soc. Annu. Meet.* **2018**, *62*, 1027–1031. [CrossRef]
37. Canhoto, A.I.; Arp, S. Exploring the factors that support adoption and sustained use of health and fitness wearables. *J. Mark. Manag.* **2017**, *33*, 32–60. [CrossRef]
38. El-Gayar, O.; Elnoshokaty, A. Factors and design features influencing the continued use of wearable devices. *J. Healthc. Inform. Res.* **2023**, *7*, 359–385. [CrossRef]
39. Adapa, A.; Nah, F.F.H.; Hall, R.H.; Siau, K.; Smith, S.N. Factors Influencing the Adoption of Smart Wearable Devices. *Int. J. Hum. Comput. Interact.* **2018**, *34*, 399–409. [CrossRef]
40. Liao, T.; Tanner, K.; MacDonald, E.F. Revealing insights of users' perception: An approach to evaluate wearable products based on emotions. *Des. Sci.* **2020**, *6*, e14. [CrossRef]
41. Davis, F.D.; Bagozzi, R.P.; Warshaw, P.R. User acceptance of computer technology: A comparison of two theoretical models. *Manag. Sci.* **1989**, *35*, 982–1003. [CrossRef]
42. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User Acceptance of Information Technology: Toward a Unified View. *MIS Q.* **2003**, *27*, 425–478. [CrossRef]
43. Fiske, S.T.; Cuddy, A.J.; Glick, P.; Xu, J. *A Model of (Often Mixed) Stereotype Content: Competence and Warmth Respectively Follow from Perceived Status and Competition*; Routledge: London, UK, 2018; pp. 162–214.
44. Kelly, N. All the world's a stage: What makes a wearable socially acceptable. *Interactions* **2017**, *24*, 56–60. [CrossRef]
45. Venkatesh, V.; Bala, H. Technology acceptance model 3 and a research agenda on interventions. *Decis. Sci.* **2008**, *39*, 273–315. [CrossRef]
46. Kelly, N.; Gilbert, S. The WEAR Scale: Developing a Measure of the Social Acceptability of a Wearable Device. In Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems, San Jose, CA, USA, 7–12 May 2016; Association for Computing Machinery: New York, NY, USA, 2016; pp. 2864–2871. [CrossRef]
47. Cuddy, A.J.; Fiske, S.T.; Glick, P. *Warmth and Competence as Universal Dimensions of Social Perception: The Stereotype Content Model and the BIAS Map*; Association for Computing Machinery: New York, NY, USA, 2008; Volume 40, pp. 61–149. [CrossRef]

48. Schwind, V.; Deierlein, N.; Poguntke, R.; Henze, N. Understanding the Social Acceptability of Mobile Devices using the Stereotype Content Model. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, Glasgow, UK, 4–9 May 2019; Association for Computing Machinery: New York, NY, USA, 2019; pp. 1–12. [CrossRef]
49. Cuddy, A.J.; Fiske, S.T.; Kwan, V.S.; Glick, P.; Demoulin, S.; Leyens, J.P.; Bond, M.H.; Croizet, J.C.; Ellemers, N.; Sleebos, E.; et al. Stereotype content model across cultures: Towards universal similarities and some differences. *Br. J. Soc. Psychol.* **2009**, *48*, 1–33. [CrossRef] [PubMed]
50. Sehrt, J.; Braams, B.; Henze, N.; Schwind, V. Social Acceptability in Context: Stereotypical Perception of Shape, Body Location, and Usage of Wearable Devices. *Big Data Cogn. Comput.* **2022**, *6*, 100. [CrossRef]
51. Profita, H.P.; Clawson, J.; Gilliland, S.; Zeagler, C.; Starner, T.; Budd, J.; Do, E.Y.L. Don't mind me touching my wrist: A case study of interacting with on-body technology in public. In Proceedings of the 2013 International Symposium on Wearable Computers, Zurich, Switzerland, 8–12 September 2013; Association for Computing Machinery: New York, NY, USA, 2013; pp. 89–96. . [CrossRef]
52. Harrison, C.; Lim, B.Y.; Shick, A.; Hudson, S.E. Where to locate wearable displays?: Reaction time performance of visual alerts from tip to toe. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*; Association for Computing Machinery: New York, NY, USA, 2009; pp. 941–944. [CrossRef]
53. Gemperle, F.; Kasabach, C.; Stivoric, J.; Bauer, M.; Martin, R. Design for Wearability. In Proceedings of the 2nd IEEE International Symposium on Wearable Computers (ISWC '98), Pittsburgh, PA, USA, 19–20 October 1998; pp. 116–122. [CrossRef]
54. GPT-4 Is OpenAI's Most Advanced System, Producing Safer and More Useful Responses. Available online: https://openai.com/index/gpt-4/ (accessed on 10 January 2025).
55. OPED-AG. VACOpedes—Orthese Mit Optimaler Druckentlastung: Für Mittel- und Vorfuß. Available online: https://oped.ch/vacopedes (accessed on 10 January 2025).
56. Enovis. AIRCAST® AIRSELECT™ Short Walker. Available online: https://www.enovis-medtech.de/AIRCAST-AIRSELECT-Short-Walker (accessed on 10 January 2025).
57. OPED-Medical-Inc. VACOcast Diabetic Boot. Available online: https://opedmedical.com/products/vacocast-diabetic/ (accessed on 10 January 2025).
58. Enovis. AIRCAST® AIRSELECT™ Achilles Walker. Available online: https://www.enovis-medtech.de/AIRCAST-AIRSELECT-Achilles-Walker (accessed on 10 January 2025).
59. Berglingstyle. FastProtect Malleo: Der Sicherheitsgurt für Dein Sprunggelenk. Available online: https://www.berglingstyle.com/products/fastprotect-malleo-5 (accessed on 10 January 2025).
60. Betterguards-Technology. The BetterGuard 1.0: Best Ankle Brace. Available online: https://betterguards.de/en/products/the-betterguard-1 (accessed on 10 January 2025).
61. Otto-Bock-HealthCare. WalkOn Reaction Lateral. Available online: https://www.ottobock.com/en-us/product/28U34 (accessed on 10 January 2025).
62. Vitego. ofa Push Ortho Fußheberorthese AFO. Available online: https://www.vitego-shop.de/bandagen-fuss-ofa-push-ortho-fussheberorthese-afo (accessed on 10 January 2025).
63. Pillai, M. Revolutionizing Healing: The Era of 3D-Printed Orthotics. 2023. Available online: https://amchronicle.com/case-studies/revolutionizing-healing-the-era-of-3d-printed-orthotics/ (accessed on 10 January 2025).
64. HfG Schwäbisch Gmünd. exoJack—Eine Smarte Orthese für Sprunggelenksbrüche. 2021. Available online: https://ausstellung.hfg-gmuend.de/w-2021/projekte/exojack-eine-smarte-orthese-fuer-sprunggelenksbrueche (accessed on 10 January 2025).
65. Fraunhofer-Institut für Werkzeugmaschinen und Umformtechnik IWU. SensO-FeeT—Sensorisch Aktive Sprunggelenk-Orthese Mit Taktiler Feedback-Technologie. Available online: https://www.iwu.fraunhofer.de/de/projekte/senso-feet-sensorisch-aktive-sprunggelenk-orthese-mit-taktiler-feedback-technologie.html (accessed on 10 January 2025).
66. Taylor, T. Sensoria's Smart Socks Measure Your Running Patterns, Improving Gait. 2015. Available online: https://www.si.com/edge/2015/03/06/sensoria-smart-socks-measure-running-patterns (accessed on 10 January 2025).
67. Orthotics, X.P. Ankle & Foot. Available online: https://xtremity.ae/ankle-and-foot/ (accessed on 10 January 2025).
68. Free3D. 3D-Gedruckter Orthopädischer Gipsverband am Bein 3D-Modell. 2024. Available online: https://free3d.com/de/3d-model/3d-printed-orthopedic-cast-on-leg-7449.html (accessed on 10 January 2025).
69. Braun, V.; Clarke, V. Using thematic analysis in psychology. *Qual. Res. Psychol.* **2006**, *3*, 77–101. [CrossRef]
70. Kassambara, A. rstatix: Pipe-Friendly Framework for Basic Statistical Tests. Available online: https://rpkgs.datanovia.com/rstatix/ (accessed on 10 January 2025).
71. Schwind, V.; Henze, N. Anticipated User Stereotypes Systematically Affect the Social Acceptability of Mobile Devices. In Proceedings of the 11th Nordic Conference on Human-Computer Interaction: Shaping Experiences (NordiCHI '20), Tallinn, Estonia, 25–29 October 2020; Shaping Society, Association for Computing Machinery: New York, NY, USA, 2020. [CrossRef]

72. Minaoglou, P.; Tzotzis, A.; Efkolidis, N.; Kyratsis, P. Integrating Artificial Intelligence into the Shoe Design Process. *Eng. Proc.* **2024**, *72*, 7. [CrossRef]
73. Zhou, K.Q.; Nabus, H. The ethical implications of DALL-E: Opportunities and challenges. *Mesop. J. Comput. Sci.* **2023**, *2023*, 16–21. [CrossRef]