Automated Usability and User Experience Assessment for Smart Products

Anoop Kumar SINHA[a], Youngmi Christina CHOI[b], and David W. ROSEN[a, 1]
[a] *Institute of High Performance Computing, A*STAR, Singapore 138632*
[b] *Design Products, Royal College of Arts, London, UK*

Abstract. The ever-increasing demand for user-centred smart products has driven the need for automation methodologies in product design processes, particularly for assessing usability and user experience (UX). Traditionally, practitioners construct functional (software) or physical (hardware) product prototypes to enable usability and UX assessments. Constructing a prototype followed by human testing are both time consuming and expensive activities. If virtual models and automated methods can replace some components of these activities, the time and cost of smart product development could be reduced while continuing to generate useful and beneficial products. In this paper, we survey the literature related to automated assessment methods for designing user-centric smart products. We identified five key activities on which to focus related to the testing or the design cycle: design thinking, design ideation, prototype creation, user data collection, and data analysis. The review methodology consisted of comprehensive search queries tailored to each activity to encapsulate automation methods pertinent to smart product development in research articles published from 2000-2023. Over 100 relevant articles were identified across engineering, human-computer interaction, human factors, industrial design, and other disciplines. This review highlights the effectiveness and limitations of various automation methods, benchmarked against traditional practice, providing valuable insights and practical recommendations for researchers and designers seeking to optimize smart product design processes for broad usability concerns. We are particularly interested in designing assistive mobility and rehabilitation devices. Development time and resources are often limited yet usability and UX directly impact important outcomes including perceived function, stigma, and device adoption. Improving these requires a transdisciplinary approach.

Keywords. Usability assessment, User experience, Smart products, Cyber-Physical-Human systems, Transdisciplinary engineering.

Introduction

Much traditional product design following conventional practices was characterized by iterative methods with minimal technology integration and minimal user participation in the design cycle before a physical prototype was created. The process often relied on brainstorming the idea of a new product or improve an existing product, physical prototyping, manual surveys for user data collection, and manual methods for user data analysis, resulting in extended development cycles and huge resource utilization. However, current principles of user centered design, enhanced user experience (UX), and inclusive design (ID) have advocated for user involvement in the design cycle to

[1] Corresponding Author, Mail: [rosendw@ihpc.a-star.edu.sg].

create successful products. Simultaneously, new and innovative methods have emerged to automate the ways in which user voice can be integrated in the design cycle.

For this work, smart products are cyber-physical-human systems (CPHS) that deliver services to the user through a user interface, while sensors and local computation read user commands and signals, then take appropriate actions. Smart products consist of three main subsystems: cyber, physical, and human. The physical subsystem consists of the product hardware, while the human subsystem comprises of the user interface, services, and the UX. The cyber subsystem consists of local computation and an optional back-end system for recording data and significant computation.

This literature review focusses on answering the question: What is the current state-of-the-art of automated assessment methods for smart products? We believe that the state-of-the-art is not well developed. But if such automated assessment methods could be developed, they could have a tremendous impact on smart product acceptability and usability. Also, we believe that good methods for user data collection and analysis have been developed but they fall short of providing needed insights into smart product acceptability and usability.

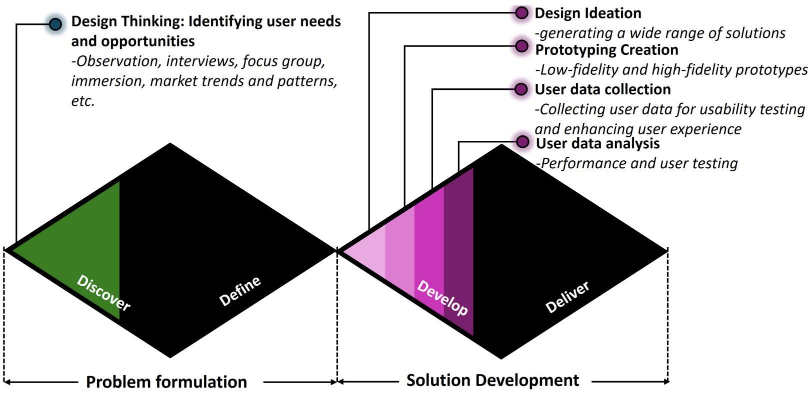

Figure 1. Activities of interest mapped onto the "double diamond" product design process.

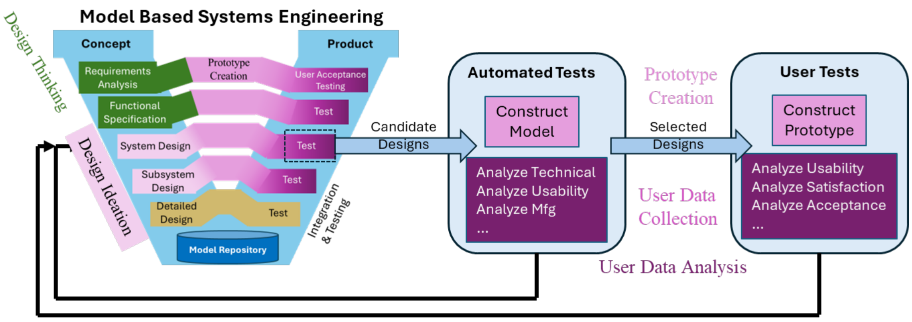

Figure 2. Proposed design framework.

Consistent with our research question, we investigate automation methods that have been incorporated at different stages in the design cycle of user-centric smart products. We have situated our survey relative to the well-known "double diamond" UX design process model [1] in Figure 1. In UX and ID, engagements with users early in product design are necessary for problem formulation and solution evaluation. We emphasize automation methods in rapidly synthesizing problem definitions from user requirements

(UR), market trends, and challenges (first diamond - Discover), and in product development (second diamond- Develop) through automation in ideation, prototype creation, user data collection, and usability analysis. We are not advocating limits on user engagement; rather, we emphasize more efficiently and effectively performing UR analysis, design solution generation, and usability evaluation. As we have identified, automation can play a major role in five key steps of the design cycle: Design Thinking (DT), Design Ideation (DI), Prototype Creation (PC), User Data Collection (UDC), and User Data Analysis (UDA). We comprehensively explore innovative automation methods used in each stage to integrate UR, preferences, and perspectives, aiming to enhance user satisfaction and acceptability of smart products. As a result, we gain insights into how user voice has been integrated into the design cycle of smart products over the past two decades through automation and can partially answer our research question.

We envision a future CPHS design framework that is built upon a model-based systems engineering (MBSE) framework with significant elements of UX design and human factors [2]. To emphasize the solution development phase of the design process, a schematic of a proposed design framework, shown in Figure 2, supports rapid design ideation and evaluation using automated methods (Automated Tests) in a short iterative loop. For selected designs, a more complete and rigorous evaluation should be performed with user tests in a longer iterative loop. Note the color coding of the five steps to show the relationships between the design framework and Figure 1. For the purposes of this paper, we focus on the shorter loop using automated methods.

1. Review methodology

We conducted a systematic review encompassing literature from 2000 to 2023 utilizing documents sourced from the Web of Science (WoS) database. Our main research query was: what methodologies of automation are employed in the design and development of user centric smart products? For each of the key steps, specific keyword-based search queries were utilized comprising of keywords such as **(“data mining” OR “machine learning”) AND (“user requirement”)** for DT, **(“generative AI”) AND (“design”)** for DI, **(“virtual”) AND (“prototype”)** for PC, **(“sensor”) OR (“user data” OR “user feedback”)** for UDC, and **(“user data” OR “user feedback”) AND (“machine learning” OR “deep learning”)** for UDA. A total of 4,206 articles were identified from the WoS database. After that, we applied inclusion and exclusion criteria, selecting articles published in English and focusing on smart products and usability studies. Articles solely focused on user interface development were excluded. This process yielded 109 articles from the WoS database. Further, a manual search on Google Scholar yielded an additional 45 articles. Hence, 154 research articles were chosen for this review.

2. Automating the design cycle of smart products

2.1. Automating design thinking

DT is crucial for understanding user needs and defining the problem a smart product will solve. However, its traditional approach can be time-consuming and resource-intensive due to extensive data gathering, user studies, and market research. To expedite this process, automation methodologies are being integrated into DT, utilizing technologies like analytical models, data mining, machine learning (ML), natural language processing (NLP), and simulation techniques.

Table 1. Automations in design thinking

Methods	Products	Data resource	Technique used
Analytical, statistical, and graph-based models	Smart sleeping service [3], Smart nursing bed [4] Walking aid for elderly [5]	Textual data [3], interviews [4], Reddit, e-commerce websites, scientific and assistive device databases [5]	ATCUL-BWM [3], KG [4], PAPDM combining evaluation grid method, Quantification Theory Type I, and TRIZ [5]
Data mining and ML	Taxi app [6], Smart cleaning robot [7], Electric bicycle service [8]	User activity [6], e-commerce: Jindong [7], public review data [8]	Doc2vwc model [6], UNISON, Bi-LSTM, BTM, Kano and opportunity model [7], SOM [8]
Data mining and NLP	Smart home systems [9], IoT devices [10], SUV car models [11]	Reddit user comments and posts [9], Twitter review data [10], consumer reviews [11]	Bidirectional encoder, Plutchik's wheel [9], Latent Dirichlet Allocation (LDA), SVM, multinomial Bayes, logistic regression (LR), random forest [10], term frequency, fasttext model [11]
Simulation suits	Upper extremity [12], full body [13], gloves [14]	Human understanding of disability from restricted movements	Impede movement to simulate disability

Various analytical, statistical, and graph-based tools have been developed to efficiently identify UR for smart products. For example, tools used include Asymmetric Trapezium Cloud-based Uncertain Linguistic BWM (ATCUL-BWM) [3], Knowledge Graphs (KG) [4], and Preference-based Assistive Product Design Model (PAPDM) [5], among others.

The integration of big data analytics and ML techniques enables smart product designers to gain understanding of UR and preferences from appropriate user data repositories. These include applying deep learning methods like Doc2Vec model [6], UNISON framework, Bi- long short-term memory (Bi-LSTM) neural networks, bi-term topic model (BTM) [7], self-organizing maps (SOM) [8], and many more.

Leveraging data mining combined with NLP allows deciphering user sentiments about a smart product. The studies [9], [10], and many more have deciphered user sentiments from user-generated content. This approach can yield a good understanding of users' emotional experiences. Additionally, dynamic UR mining methodologies using NLP techniques have been proposed [11]. These studies underscore the significance of continually adapting and evolving products based on dynamic UR and extracted user knowledge, contributing to more user-centric design approaches.

Simulation suits, wearable devices that replicate physical conditions or impairments, enhance understanding and empathy towards user needs in design. Examples include KINdRed [12] for upper extremity disability simulation and GERT [13] for full-body impairment simulation. Other tools like the Cambridge simulation gloves [14] and glasses [15] simulate limitations in hand movement and vision loss, enabling designers to assess accessibility and create more inclusive designs. Simulation suits also enable recording sensor data during usage to enhance their value, although the data will not be as good as those from actual users. Table 1 shows the various automation methods used for different smart products and types of data resource.

Table 2. Automations in design ideation

Product	User	Technique	Input data	Metrics
Bike saddle [16]	Bike users	GAN	Forces and shape	User preference
Virtual aircraft model [17]	Designed for all	GAN	Point cloud from 3D models	Drag coefficients
Robotic manipulator [18]	Cyber physical production system	Shape generation in Autodesk	Design parameters (DP)	Forces, weight, and time
Flapping wing air vehicle [19]	Designed for air vehicle	Bio-inspired GD	Wing DP and flight conditions	Lift, flight speed
Spinal orthosis [20]	Upper body disability patients	Fusion 360	DP, material (M), manufacturing technology (MT)	Production cost, mechanical properties (MP)
Knee implant [21]	Knee disability	GSO	DP, M, MT	MP
Elbow orthosis [22]	Elbow issues	Grasshopper	DP, M, MT	MP
Prosthetic foot [23]	Ambulated patients	Fusion 360	Forces. mass, MT	Safety factor, cost
Maxillofacial implants [24]	Patients requiring surgery	Field driven GD in nTopology	DP and surgical process	Computation time, stress area

2.2. Automating design ideation

Generative AI and generative design (GD) are revolutionizing the field of design ideation by automating the creation of countless design variations based on predefined parameters and constraints. With GD, designers can input specific parameters and constraints, allowing AI to independently generate multiple designs. Traditionally, GD has been used to propose alternative design solutions for products, specifically focusing on the architecture, aesthetics, and mechanical components of the product. For instance, it has been applied in shape synthesis and topology optimizations for bike saddles [16]. Further, it has demonstrated progress in the design of smart products such as 3D virtual aircraft [17], connection links of a robot manipulator [18] , and aerial vehicle flapping wings [19].

In the literature, impactful use cases of GD for smart products have emerged in the biomedical industry, including creation of a personalized vertebral body [20] using GD in Fusion 360 and a knee joint implant [21] through Generative Structure Optimization (GSO). Similarly, GD in Grasshopper has been employed to develop aesthetically appealing, customized designs for elbow orthosis [22]. Several passive exoskeletons and prosthetic devices for example, a passive prosthetic foot for patients with ambulation [23] and implants for maxillofacial surgery [24] have been designed by GD. GD has also been applied extensively in the aerospace and additive manufacturing domains. Table 2 shows various types of smart products and generative techniques that have been identified in literature. Note that GAN denotes Generative Adversarial Network, a type of convolutional neural network in the machine learning field.

2.3. Automating prototype creation

Virtual reality (VR) and Augmented Reality (AR) have gained significant popularity as virtual prototyping technologies before physical manufacturing. Several research projects highlight their significance as cost effective and faster methods for prototyping in evaluating user interactions with smart products such as in smart home appliances [25], car models [26], and also in creating virtual training environments for smart factories

[27]. In the biomedical industry, VR and AR systems have been utilized for developing immersive and highly engaging rehabilitation systems, aiding patients after treatment, for example after breast cancer surgery [28] and stroke [29]. Such methods improve attention, memory, and motor coordination in patients and also enhance the UX. Additionally, Tangible Augmented Reality (TAR) has been used to evaluate usability of smart products with physical interface controls [30]. Table 3 shows the hardware requirements, characteristics, and applications of virtual prototyping.

Table 3. Automations in prototype creation

Method	Characteristics	Hardware required	Platforms
VR	Fully immersive	VR headsets, motion controllers, room scale tracking systems, gaming PC or consoles, VR compatible headphones, haptic feedback devices	3DVIA [25, 26], Unity 3D [27]
AR	Semi-immersive	Smartphones/tablets, AR glasses such as HoloLens, Magic leap one etc., Head mounted display, wearable sensors	Unity 3D, Zapworks [28, 29]
TAR	Tangible interaction by physical- digital integration	Tangible objects, depth sensing cameras, computing devices such as tablets/ smartphones, display devices such as screens or projectors	Vuforia [30]

2.4. Automating user data collection

This stage involves gathering user interaction data to detect usability issues. Traditionally, user data for usability testing was collected through subjective questionnaires and user testing, but automation techniques have enhanced the depth and quality of information gathered in recent years.

Capturing user activity and action sequences provides real-time quantitative data on user engagement, reaction, mental workload, distractions, and ease of use. Various sensors such as eye tracking [31, 32], accelerometers, inertial motion units (IMU) [33], and dynamometers [34] have been integrated into smart products to collect user activity data for usability testing. Sensors also capture user psychological and physiological response to smart product interactions; sensors include electroencephalogram (EEG), electrocardiogram (ECG), electromyography (EMG), electrodermal activity (EDA) sensors, and temperature sensors [35], [36], [37]. These data offer insights into real-time user emotions, cognition, and experiences with smart products, facilitating quantitative usability analysis, albeit limited. Additionally, novel methods for user data collection, such as Functional Near-infrared Spectroscopy (fNIR) and oxygen levels in the brain (HbO2), have been employed in some research [38]. Table 4 shows the different types of sensors and their purpose in usability studies.

2.5. Automating user data analysis

This stage involves analyzing the collected data to identify patterns and trends, and to inform further design iterations. The emergence of automated data analysis techniques, powered by analytical tools, ML, and NLP has opened new doors for a truly data-driven design approach for evaluating usability and UX (see Table 5).

Analytical tools such as USEMATE [39] and Active story [40] have been proposed as automated usability testing tools. Additionally, statistical techniques such as Partial Least Squares Structural Equation Modeling have been used to assess user satisfaction and engagement [41]. ML offers advantages over analytical tools for handling large and diverse data sets. Algorithms such as SVM, neural networks (NN), and decision trees (DTree) analyzed user satisfaction and UX across various smart products [42]. Further, ML combined with facial recognition and audiovisual data has been used to enhance usability prediction [43]. Several studies have reported utilizing ML in developing adaptive assistive technologies for improving real-time UX. Based on physiological signals combined with ML, rehabilitation systems were adjusted to make the system engaging and useful [44].

NLP and sentiment analysis further expands the range of analyzable data. Several sentiment classifiers such as Recurrent Neural Network (RNN), LSTM, Naïve Bayes (NB), KNN, Logistic Regression, Light Gradient Boosting Machine (LightGBM), Categorical boosting algorithm (Catboost), and Valence Aware Dictionary and sEntiment Reasoner (VADER) have been proposed and implemented to test the effectiveness of novel smart products [45], [46]

Table 4. Automations in user data collection

Data type	Sensor type	Smart product tested	Purpose	Platform/tools
Activity tracking sensors	Eye tracking [31, 32] IMU [33] Dynamometer [34]	Smart factory process Gait monitoring insole Assistive aid for hand	Visual attention User motion Grip strength	Tobii glass and iMotion [31,32] Custom GUI [33]
Physiological sensors	EMG [35] ECG, EDA [36]	Knee assistive device Mobile app	Muscle effort Heart rate, skin conductance	Unity GUI [35] -
Psychological sensors	EEG [37] HbO2, fNRI [38]	Touch based system Smart glove	Brain activity O_2 level in brain	- NIRSscout [38]

Table 5. Automations in user data analysis

Method	Smart product	Data resource	Technique used
Analytical	USEMATE tool itself [38] Low fidelity prototypes [39]	Task operation data (TOD) Prototype designer tool	USEMATE Active story
ML based	Surgical robot [41] Agriculture digital tool [42] Adaptive rehabilitation [43]	TOD and environment data Audio visual data Pulse rate, respiration rate, EDA, and temperature	SVM., NN, DTree YOLO LR, SVM, NB, KNN
NLP based	E-distance learning [44] RoBlox metaverse app [45]	Twitter data Google play reviews	RNN and LSTM NB, KNN, LR, LightGBM, Catboost, VADER

3. Automation challenges and limitations

Design Thinking: Incorporating all stakeholder voices is challenging due to diverse priorities, practices, and vocabulary. Thus design decisions often consider contexts, cultural aspects, and social implications of the product. Automation tools in DT struggle to integrate these aspects. Additionally, unstructured data from user reviews, ratings, and data repositories present another hurdle.

Design Ideation: Recent advancements in generative design technologies in engineering domains are potent but narrowly focused. Even cutting-edge AI tools like ChatGPT, Dall'e, and Sora have notable limitations. Sora's generated videos are realistic and emotive but lack comprehensive physics and analytical capabilities. Notably, DI methods and tools often overlook the human subsystem in CPHS.

Prototype Creation: Many technical challenges exist in developing physical prototypes or virtual models of smart products since they are often complex mechatronic systems. Prototypes and models are inherently incomplete, typically emphasizing specific aspects of the product for testing specific functions. Notably, good technologies and tools are available for testing prototypes, but prototype creation is still largely a manual process that requires time and funding. Matching model completeness, technical fidelity, and user interaction sophistication to the purposes of testing is very difficult.

User Data Collection: For UDC with physical prototypes, the devices need to interact with user's bodies, which raises fidelity, ergonomics, and safety issues. It also constrains users to be physically collocated with the testing facility. Set-up costs for suitable test facilities can be high. Sensors such as EEG and ECG can generate huge amounts of data that can be challenging to store, process, analyze, and interpret. Since data collection is needed but time consuming, experiments and data collection should be optimized to collect only what is needed and to leverage the data as much as possible. Analysis and interpretation can require specialized expertise that may not be available.

User Data Analysis: Datasets for ML and NLP methods are often unstructured; significant efforts may be needed to properly structure them for ML. Some data for NLP can be ambiguous or vague. Existing datasets for training may be incomplete, biased, or otherwise not applicable for types of smart products. Sensor data can be voluminous, but difficult to analyze or have a low signal-to-noise ratio. When multiple data sources are available, data often must be combined, or fused, which can raise other challenges. General relationships between analyzed data and human emotional responses, decisions, and product acceptability, etc. remain uncertain.

4. Research issues and conclusions

The survey and analysis reveal crucial research gaps. Addressing these gaps can propel automation in design processes, enhancing efficiency and effectiveness in user-centric smart product development.

The reviewed automation methods lack comprehensive models of human perception, physical reactions, emotions, and decisions, essential for evaluating product usability, satisfaction, and acceptability. There has not been an effort to capture human behaviors and emotions to support Design Thinking or product design evaluation. Additionally, no similar framework to the proposed design in Figure 2 has been explored, and the concept of automated product evaluation for usability and acceptability analysis remains unexplored. Despite the growing body of literature on CPHS, a thorough treatment of the human element has not been demonstrated yet.

More specific research issues are also evident from our review: (1) Research is needed to develop automation techniques that effectively incorporate the diverse stakeholder perspectives throughout the design cycle; (2) Automation to complement and enhance human creativity, empathy, and critical thinking in DT and user-centered practices, rather than replacing essential human aspects of the design process, is needed; (3) Automated methods to effectively handle unstructured data sources, such as qualitative feedback, images, and user narratives, are needed; (4) Interdisciplinary research is needed to address the challenges of automating PC, including seamless integration of mechanical, electronic, software, and user interface components; (5) Research gaps exist in automated user data collection that ensures user engagement, handles the vast amount of data while maintaining data quality and reliability; (6)

Methods are needed for integrating and analyzing large datasets from diverse sources in UDA, to gain a comprehensive understanding of UX and preferences.

CPHS are complex systems that attempt to seamlessly integrate mechanical, electronic, software, and user interface components, while considering human actions, responses, and decisions and other product life-cycle considerations, including manufacturing constraints, repair, upgrade potential, material recyclability, etc. Due to the complex, interdisciplinary nature of CPHS, the CPHS field requires treatment as a transdiscipline, not just a collection of loosely coupled disciplines.

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References

[1] "Design council," https://www.designcouncil.org.uk/our-resources/the-double-diamond/.

[2] D.W. Rosen and C. Choi, "A Design Framework for Cyber-Physical-Human-Systems.," In: P. Koomsap, A. Cooper, and J. Stjepandić, Eds. *Advances in Transdisciplinary Engineering*. *IOS Press* (2023).

[3] T. Zhou, Z. Chen, Y. Cao, R. Miao, and X. Ming, "An integrated framework of user experience-oriented smart service requirement analysis for smart product service system development.," *Advanced Engineering Informatics*. vol. 51, p. 101458, 2022.

[4] X. Li, C.-H. Chen, P. Zheng, Z. Wang, Z. Jiang, and Z. Jiang, "A Knowledge Graph-Aided Concept–Knowledge Approach for Evolutionary Smart Product–Service System Development.," *Journal of Mechanical Design*. vol. 142, no. 10, p. 101403, 2020.

[5] B. Zhang, M. Ma, and Z. Wang, "Promoting active aging through assistive product design innovation: a preference-based integrated design framework.," *Frontiers in Public Health*. vol. 11, p. 1203830, 2023.

[6] M.-C. Chiu, J.-H. Huang, S. Gupta, and G. Akman, "Developing a personalized recommendation system in a smart product service system based on unsupervised learning model.," *Computers in Industry*. vol. 128, p. 103421, 2021.

[7] K. Zhang, K.-Y. Lin, J. Wang, et al., "UNISON framework for user requirement elicitation and classification of smart product-service system.," *Advanced Engineering Informatics*. vol. 57, p. 101996, 2023.

[8] J. Cong, C.-H. Chen, X. Meng, Z. Xiang, and L. Dong, "Conceptual design of a user-centric smart product-service system using self-organizing map.," *Advanced Engineering Informatics*. vol. 55, p. 101857, 2023.

[9] J. Wang and Y.-L. Liu, "Deep learning-based social media mining for user experience analysis: A case study of smart home products.," *Technology in Society*. vol. 73, p. 102220, 2023.

[10] J.R. Saura, D. Palacios-Marqués, and D. Ribeiro-Soriano, "Using data mining techniques to explore security issues in smart living environments in Twitter.," *Computer Communications*. vol. 179, pp. 285–295, 2021.

[11] H. Sun, W. Guo, H. Shao, and B. Rong, "Dynamical mining of ever-changing user requirements: A product design and improvement perspective.," *Advanced Engineering Informatics*. vol. 46, p. 101174, 2020.

[12] J. Armstrong, R. Stone, S. Immel, and K. Hunter-Zaworski, "A Validation Study of Disability Simulation Suit Usage as a Proxy for Customer Need Statements From Persons With Disabilities.," In: *Volume 7: 27th International Conference on Design Theory and Methodology*. pp. V007T06A046. *American Society of Mechanical Engineers*, Boston, Massachusetts, USA (2015).

[13] "Full body simulation suit GERT," https://www.age-simulation-suit.com/.

[14] "Cambridge simulation glove," https://www.inclusivedesigntoolkit.com/gloves/gloves.html.

[15] "Cambridge simulation glasses," https://www.inclusivedesigntoolkit.com/csg/csg.html#nogo.

[16] Z. Jiang, H. Wen, F. Han, Y. Tang, and Y. Xiong, "Data-driven generative design for mass customization: A case study.," *Advanced Engineering Informatics*. vol. 54, p. 101786, 2022.

[17] D. Shu, J. Cunningham, G. Stump, et al., "3D Design Using Generative Adversarial Networks and Physics-Based Validation.," *Journal of Mechanical Design*. vol. 142, no. 7, p. 071701, 2020.

[18] E. Francalanza, A. Fenech, and P. Cutajar, "Generative design in the development of a robotic manipulator.," *Procedia CIRP*. vol. 67, pp. 244–249, 2018.

[19] Z. Jiang, Y. Ma, and Y. Xiong, "Bio-inspired generative design for engineering products: A case study for flapping wing shape exploration.," *Advanced Engineering Informatics*. vol. 58, p. 102240, 2023.

[20] R. Murzac, C. Doicin, and M. Ulmeanu, "Data Acquisition and Generative Design for a Smart Spinal Orthosis.," *Macromolecular Symposia*. vol. 396, no. 1, p. 2000297, 2021.

[21] J. Xu, K. Wang, M. Gao, Z. Tu, S. Zhang, and J. Tan, "Biomechanical performance design of joint prosthesis for medical rehabilitation via generative structure optimization.," *Computer Methods in Biomechanics and Biomedical Engineering*. vol. 23, no. 15, pp. 1163–1179, 2020.

[22] V. Ricotta, R.I. Campbell, T. Ingrassia, and V. Nigrelli, "A new design approach for customised medical devices realized by additive manufacturing.," *International Journal on Interactive Design and Manufacturing (IJIDeM)*. vol. 14, no. 4, pp. 1171–1178, 2020.

[23] M. McGuire, "Generative design of an additively manufactured passive prosthetic foot for multiple forms of ambulation.," p. 2022.

[24] A. Tel, E. Kornfellner, F. Moscato, et al., "Optimizing efficiency in the creation of patient-specific plates through field-driven generative design in maxillofacial surgery.," *Scientific Reports*. vol. 13, no. 1, p. 12082, 2023.

[25] M. Bordegoni and F. Ferrise, "Designing interaction with consumer products in a multisensory virtual reality environment: This paper shows how Virtual Reality technology can be used instead of physical artifacts or mock-ups for the new product and evaluation of its usage.," *Virtual and Physical Prototyping*. vol. 8, no. 1, pp. 51–64, 2013.

[26] F. Shao, A. J Robotham, and B. K K Hon, "Development of a 1:1 Scale True Perception Virtual Reality System for design review in automotive industry.," Presented at the 10th International Conference on Manufacturing Research ICMR 2012 (2012).

[27] P. Zawadzki, K. Zywicki, P. Bun, and F. Gorski, "Employee Training in an Intelligent Factory Using Virtual Reality.," *IEEE Access*. vol. 8, pp. 135110–135117, 2020.

[28] Z. Zhou, J. Li, H. Wang, Z. Luan, Y. Li, and X. Peng, "Upper limb rehabilitation system based on virtual reality for breast cancer patients: Development and usability study.," *PLOS ONE*. vol. 16, no. 12, p. e0261220, 2021.

[29] F.-C.-S.F. Kow, A.K. Sinha, Z.J. Ming, et al., "MIDAS: Multi-sensorial Immersive Dynamic Autonomous System Improves Motivation of Stroke Affected Patients for Hand Rehabilitation.," p. 2022.

[30] Y.M. Choi, "Applying Tangible Augmented Reality for Product Usability Assessment.," *Journal of Usability Studies*. vol. 14, no. 4, pp. 187–200,.

[31] M. Peruzzini, F. Grandi, and M. Pellicciari, "Benchmarking of Tools for User Experience Analysis in Industry 4.0.," *Procedia Manufacturing*. vol. 11, pp. 806–813, 2017.

[32] R.K. Khamaisi, A. Brunzini, F. Grandi, M. Peruzzini, and M. Pellicciari, "UX assessment strategy to identify potential stressful conditions for workers.," *Robotics and Computer-Integrated Manufacturing*. vol. 78, p. 102403, 2022.

[33] F. Lin, A. Wang, Y. Zhuang, M.R. Tomita, and W. Xu, "Smart Insole: A Wearable Sensor Device for Unobtrusive Gait Monitoring in Daily Life.," *IEEE Transactions on Industrial Informatics*. vol. 12, no. 6, pp. 2281–2291, 2016.

[34] B. Radder, G.B. Prange-Lasonder, A.I.R. Kottink, et al., "Home rehabilitation supported by a wearable soft-robotic device for improving hand function in older adults: A pilot randomized controlled trial.," *PLOS ONE*. vol. 14, no. 8, p. e0220544, 2019.

[35] C.-H. Chang, W.-C. Lien, T.-P. Chiu, et al., "A novel smart somatosensory wearable assistive device for older adults' home rehabilitation during the COVID-19 pandemic,." *Frontiers in Public Health*. vol. 11, p. 1026662, 2023.

[36] B. Myroniv, C.-W. Wu, Y. Ren, A. Christian, E. Bajo, and Y.-C. Tseng, "Analyzing User Emotions via Physiology Signals.," *Data Science and Pattern Recognition*. vol. 1, no. 2, p. 2017.

[37] J. Frey, M. Daniel, J. Castet, M. Hachet, and F. Lotte, "Framework for Electroencephalography-based Evaluation of User Experience.," In: *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. pp. 2283–2294. *ACM*, San Jose California USA (2016).

[38] S. Shin, H.-J. Lee, W.H. Chang, S.H. Ko, Y.-I. Shin, and Y.-H. Kim, "A Smart Glove Digital System Promotes Restoration of Upper Limb Motor Function and Enhances Cortical Hemodynamic Changes in Subacute Stroke Patients with Mild to Moderate Weakness: A Randomized Controlled Trial.," *Journal of Clinical Medicine*. vol. 11, no. 24, p. 7343, 2022.

[39] W.F.W. Ahmad, S. Sulaiman, and F.S. Johari, "Usability Management System (USEMATE): A web-based automated system for managing usability testing systematically.," In: *2010 International Conference on User Science and Engineering (i-USEr)*. pp. 110–115. *IEEE*, Shah Alam (2010).

[40] A. Hosseini-Khayat, T.D. Hellmann, and F. Maurer, "Distributed and Automated Usability Testing of Low-Fidelity Prototypes.," In: *2010 Agile Conference*. pp. 59–66. *IEEE*, Nashville, TN, USA (2010).

[41] R. Pan, Z. Qin, L. Zhang, L. Lou, H. Yu, and J. Yang, "Exploring the impact of intelligent learning tools on students' independent learning abilities: a PLS-SEM analysis of grade 6 students in China,." *Humanities and Social Sciences Communications*. vol. 10, no. 1, p. 558, 2023.

[42] J. Cong, P. Zheng, Y. Bian, C.-H. Chen, J. Li, and X. Li, "A machine learning-based iterative design approach to automate user satisfaction degree prediction in smart product-service system.," *Computers & Industrial Engineering*. vol. 165, p. 107939, 2022.

[43] M. Čejka, J. Masner, J. Jarolímek, et al., "UX and Machine Learning – Preprocessing of Audiovisual Data Using Computer Vision to Recognize UI Elements.," *Agris on-line Papers in Economics and Informatics*. vol. 15, no. 3, pp. 35–44, 2023.

[44] F.J. Badesa, R. Morales, N. Garcia-Aracil, J.M. Sabater, A. Casals, and L. Zollo, "Auto-adaptive robot-aided therapy using machine learning techniques.," *Computer Methods and Programs in Biomedicine*. vol. 116, no. 2, pp. 123–130, 2014.

[45] R. Sadigov, E. Yıldırım, B. Kocaçınar, F. Patlar Akbulut, and C. Catal, "Deep learning-based user experience evaluation in distance learning.," *Cluster Computing*. vol. 27, no. 1, pp. 443–455, 2024.

[46] S. Hong Lee, H. Lee, and J. Hyun Kim, "Enhancing the Prediction of User Satisfaction with Metaverse Service Through Machine Learning.," *Computers, Materials & Continua*. vol. 72, no. 3, pp. 4983–4997, 2022.