INTERNATIONAL DESIGN CONFERENCE – DESIGN 2024
https://doi.org/10.1017/pds.2024.11

A proposed framework for data-driven human factors evaluation

Isabelle Ormerod ✉, Henrikke Dybvik, Mike Fraser and Chris Snider

University of Bristol, United Kingdom

✉ isabelle.ormerod@bristol.ac.uk

Abstract

Human-centred approaches within the design cycle are crucial to enhance usability and inclusivity of products. However, the qualitative nature of traditional human factors evaluation can create bottle necks, prompting the need for more data driven methods. A framework for data-driven human factors is presented, looking to integrate mixed-method approaches. Case studies illustrate its usage in real-world scenarios and challenges are summarised, calling for robust data collection methods, balancing of mixed methods, a need for explainable systems, and interdisciplinary expertise.

Keywords: human-centred design, inclusive design, data-driven design

1. Introduction

Human-centred design is a well-recognised philosophy, that aims to make interactive systems more usable for the intended user population (Giacomin, 2015). Working with users to define their needs, the tasks at hand and the environment in which activities will take place is crucial to this process. To understand the potential interpretations of designed technology, product development teams should be interdisciplinary, considering the involvement of users throughout each stage, iteratively moving towards the best available solution (ISO 9241-210:2019). As the landscape of computational systems and sensing technologies expands, the ways we manufacture and explore parameterised design spaces have been enhanced, speeding up design iterations. However, the lengthy qualitative techniques currently used to incorporate human factors (HF), create bottlenecks when aiming to create inclusive designs (Whitefield et al., 1991). This presents a need to shift how we evaluate HFE, and an opportunity to integrate quantitative data driven approaches into human factors evaluation (HFE). Employing these techniques, more data to objectively analyse human interaction can be generated, whilst keeping up with the need for rapid design iteration.

HF is a vital part of the design process, utilising human psychology and physiology to understand human understanding and limitations when interacting with interfaces (Thales Group, 2023). Without this, systems can be designed that are unusable, and potentially dangerous systems for the people that are designed for. This is especially true within the context of medical products e.g. syringes and inhalers, where designers are commonly designing for user groups with limited dexterity or cognitive understanding. In the case of injection devices, complex and dextrous user steps to ensure sterility, as well as fatal consequences if operated incorrectly, mean that rigid due diligence is needed to identify risks and ensure safe and effective use (ISO 13485:2016, p.13). Similarly, assessments of HF and ergonomics within the workplace is legislatively enforced (HSE, 2013). This covers the design of equipment and devices, such as control boards and manual handling equipment, to the available ventilation and lighting within a space, that may otherwise induce unnecessary stress to the working environment. This occurs on an individual basis, helping to optimise work setups for individuals and ensure their safety and comfort (HSE, 2023). In contrast, leveraging HF to understand what contributes to enhanced performance can lead to superior product development. This is shown through the evolution of professional sports gear, where the evaluation and comprehension of crucial performance indicators and specific user needs across the years has led to groundbreaking records (Caine et al., 2012).

However, traditional HFE has evaded the usage of sensors to measure or quantify our responses in relation to how we feel interacting with everyday products (Kanis, 1998). This interpretation has permeated the methods in which we explore human-centred design, typically incorporating minimal quantitative methods (ISO 13485:2016). Traditional quantitative metrics such as anthropometric measurements or assessments of static body positioning and loading are often far removed from the problem at hand (Whitefield et al., 1991), limiting their applicability. However, since the development of these techniques, sensor technology and AI techniques have rapidly expanded the scope of user data that could be utilised in HFE. Exploring the potential of these systems in a systematic way and integrating this with qualitative insight to ensure a human in the loop approach, could lead to a more succinct process to help design inclusive and specialised products.

This point in time marks an opportune moment to redefine our perspective on HF. Advances in manufacturing, notably 3D printing, enable quicker, cost-effective, and flexible prototyping. Concurrently, AI-driven design techniques accelerate ideation cycles, yet without parametrisation will struggle to integrate human needs (Valdez et al., 2021). Leveraging insights from AI systems to deepen understanding of simple sensor outputs presents a significant opportunity to enhance our understanding of HF in design.

Within this paper, a proposed operational framework for data-driven HF approaches is presented. Firstly, current HFE methods are examined, highlighting the potential of quantifiable data in modelling human error. Current HFE techniques are reviewed, revealing limitations in providing rapid and detailed insights simultaneously. Utilising these findings, the framework is presented, looking to shift HFE towards a condition-based monitoring strategy, while balancing input from stakeholders and qualitative approaches. Validated through two case studies, the framework underscores the importance of including experts in data collection, synthesis, and HF. The prospects and challenges that were drawn out of this are discussed, addressing the difficulties with interoperability of data, and developing transparent and explainable systems.

2. Background

Within this section, current HFE procedures and the tensions integrating these into the design cycle are discussed. Alongside this, an overview of inclusive design principles is given, showcasing the key human abilities that should be mapped against product demands, helping to direct potential future development. While we typically image human behaviour as unpredictable, this is juxtaposed by the succinct way human error is modelled, showcasing the potential for quantifying these interactions. Next, the methods we currently use to identify error and conduct ergonomic assessments are examined. Gaps in how we're relaying relevant information back to decision makers are found, and that real-time sensing could provide detail that is currently unattainable.

2.1. Current HFE procedure

HF is an all-incorporating term that refers to the application of psychological and physiological principles to engineering to the design of products, processes and systems (Wickens et al., 2002). Within (Reason, 1990), it states that in order to analyse potential human errors, both the conditions in which an error may occur in and the particular form it might take should be investigated. These authors discuss 3 main areas that are important when evaluating the usability of a product, relating to the environment, task, and user base. For example, the environment will affect several things that relate to usability, such as clinically controlled settings compared to a busy, noisy, moving vehicle which can make a task much more difficult to complete. The user interface incorporates all aspects of the product the user will interact with, including installation, operation, and maintenance. A non-exhaustive list of these interrelating factors is displayed in Figure 1a).

The individual factors displayed showcase a multitude of potentially measurable physical capabilities and specific skill sets that must be considered for successful product interaction. In (University of Cambridge, 2023), the cycle of product interaction is summarised, illustrating that inclusive design

https://doi.org/10.1017/pds.2024.11 Published online by Cambridge University Press

principles can guide what useful physiological data can be captured that is pertinent to product interaction. This firstly involves sensory capabilities (perceive stimuli), followed by the ability to process information (think about the intended action), and then utilise their motor skills (carry out the intended action). For a successful product interaction, these combined capabilities of individuals within the given environment must be considered. As further demonstrated in (Fletcher, 2023), there are still a number of individual factors that will not be able to be captured by measurement of physical capabilities such as cultural differences, economic situation and social factors.

In (Reason, 1990), it discusses that while the intricacies of human actions make it seem unlikely for all error varieties to be captured, error can be modelled in a limited number of forms. Their interpretation first evaluates user intention, if user's actions proceed as planned, and if they achieved their desired end. This gives form to two error types, slips: where actions are mis-performed, and mistakes: where the plan to execute an action is inadequate. A more detailed summary is displayed in Figure 1b).

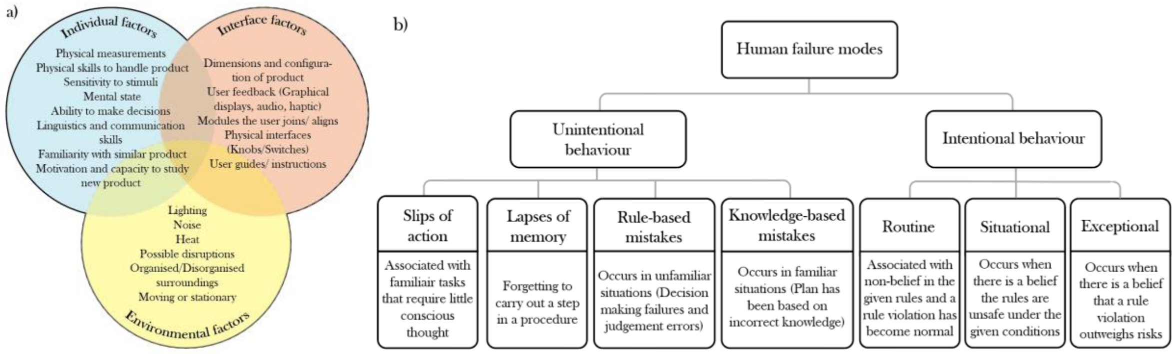

Figure 1. a) Inter-relating factors that influence product interaction adapted from (HSE, 2007) and (Imam, 2023); b) Human failure modes adapted from (Reason, 1990) and (HSE, 2007)

This modelling of human error underpins current theory, utilised in government guidance of the design of safe working conditions (HSE, 2007) and medical product design (ISO 13485:2016). While there is overlap between the inter-relating factors, the ways we model human error is succinct, suggesting viability of quantification and categorisation of human error. Considering the product and the environment, data driven techniques that explore an individual's perception of stimuli, processing abilities and motor skills are the most likely to enable better product interaction. However, analysing human error and integrating user needs into the design cycle is currently a challenging process.

2.2. Incorporating HF into the design cycle

In (Maher and Poon, 1996), the concept of the design cycle is described as a traverse between the 'problem space' and the 'solution space'. Over time, these two spaces converge with problems leading to a solution or solutions refocussing the problem. This creates tensions between both spaces. This is particularly true for integrating HF into the design cycle. In (Steen, 2011), the conflict between project-team members and users is described, where methods to communicate at different stages of the design stage must be done effectively, and must adapt to the problem presented. Additionally, this must be done in a timely manner. In (Knott, 2001), the speed and frequency of the design cycle is equated with better outcomes. Within a given time frame, if more product interactions can occur, the closer the convergence of the design and problem spaces. In the context of human-centred design, this means that methods to obtain user feedback must be quick and retain detail, reducing the speed and increasing the depth of knowledge gained in each design iteration. To evaluate and improve how this is currently being achieved within HFE, we must first understand the shortcomings of modern practice.

2.3. HFE tools

To facilitate an understanding of current HFE limitations, an assessment of techniques was conducted. Techniques gathered focus on occupational health and medical device design, two areas where user-centred design is mandated by regulatory bodies (ISO 13485:2016, ISO 6385:2016, ISO 9241-210:2019, ISO 11228-1:2021), calling for systematic exploration of user and worker needs throughout the design

https://doi.org/10.1017/pds.2024.11 Published online by Cambridge University Press

process. Based on the constraints of the design process as summarised in section 2.2, techniques were assessed based on their level of insight and the time of implementation. This approach is an adaptation of the framework presented by (Whitefield et al., 1991), which states that observational HF techniques tend to tension experiment time and expertise needed. Figure 2 maps the relationship across techniques, as well as showing if techniques are qualitative or quantitative.

In general, the qualitative techniques provide an in-depth view of the user groups, their potential interpretations and the errors that could occur. In order to gain deep insight, detailed prototypes are often required, to allow for the assessment of haptics and complexity of user steps (Scherer and Rose, 2023). Obtaining insight from users is restricted by the techniques and feedback available with lower fidelity prototype and a lengthy analysis procedure that occurs in user trials. Therefore, other methods tend to incorporate some empirical evidence, but similarly struggle to collate findings in a timely manner.

The qualitative tools assessed are generally used to evaluate the risks of long-term injury (work-related muscular skeletal disorders). It was found while these tools are intuitive to implement, in many cases there is large variation in scores and outputs even when applied to the same task (Joshi and Deshpande, 2019). These tools tend to consist of surveys and questionnaires, utilising check boxes and Likert scales to interpret user preferences reducing their fidelity and the user feedback possible. Ergo-simulation tools (Blanchonette, 2010) and Digital Human Modelling (DHM) (Wolf et al., 2020) have the potential to monitor human positioning, incorporate static human muscular skeletal modelling, and fields of vision into a simulated space, but requires accurate modelling of the user and environment , tending to simplify the problem limiting their applicability

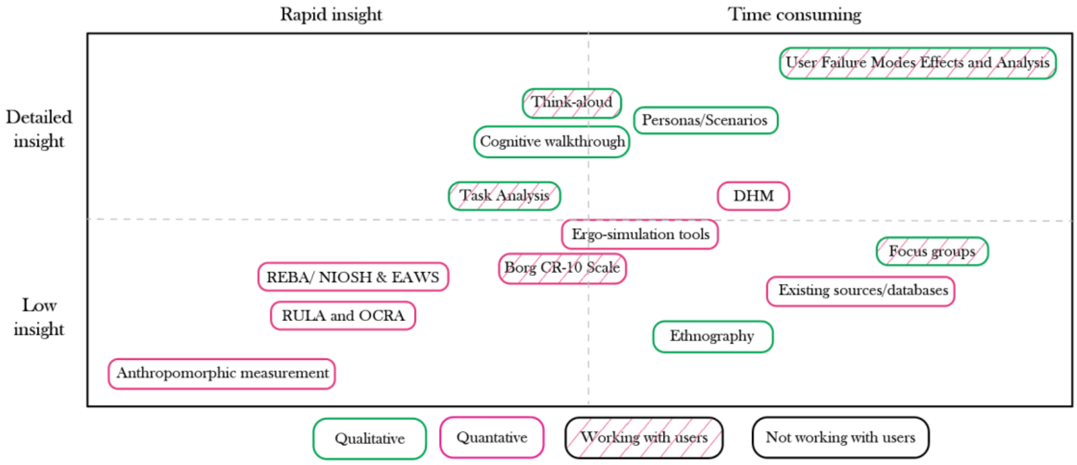

Figure 2. A mapping of HFE techniques based on level of insights and implementation time

This analysis shows there are few techniques that fulfil the need for rapid and detailed insights. Qualitative tools are more time consuming but benefit from detailed user feedback and inclusion of experts in user experiment design, HF, and mechanical designers. The logistics of user trials, synthesis of data and findings, interpreting potential failures, and modifying products, all iteratively repeated, lends itself for a lengthy product cycle. The quantitative tools discussed are generally used as quick exercises to assess risk, and do not always involve experts in HF, meaning insights ayre on the side of oversimplification. The abstraction from the problem at hand and lack of interdisciplinary team lowers the amount of insight available.

By exploring techniques that monitor individual users and incorporating expert opinions, a large amount of objective data may quickly be produced and interpreted effectively. The development of real-time sensing, combined with novel manufacturing could lead to in-situ product changes, deepening product understanding and reducing the number of iterations. In-situ testing could help isolate the understanding of additional environment factors that are relevant to product interaction. In Figure 1a), the potential factors that influence user's abilities to interact with products are stated. Recognizing the multitude of influencing factors, pinpointing the most relevant is vital for inclusive design, especially regarding vulnerable user groups. Focusing efforts on this identification allows for strategic prioritization in research and development.

https://doi.org/10.1017/pds.2024.11 Published online by Cambridge University Press

2.4. Reflection

The research above highlights that error modelling can be succinct and potentially quantifiable. To optimize product development, iteration cycles should yield rapid and detailed insights. While current HF methods face challenges in achieving this balance, assessing their strengths and weaknesses can inform the development of methods that provide faster and more objective data. Qualitative techniques, despite requiring time and expert interpretation, offer rich data for informed decision-making and relevant product changes. In contrast, quantitative data, though quicker to analyse, may lack the depth of user insights. Both approaches contribute strengths, that can be utilised to provide a more well-rounded HFE approach. Additional insight into inclusive design approaches show us that different processes are required to interpret a product, which will change based on the interface and environment.

3. Proposed data driven human factors framework

Current HFE practices struggle to contribute both quick and insightful product iteration cycles, leaving the field at an impasse. Qualitative techniques are detailed but struggle with timely information synthesis, and while quantitative techniques offer quick and objective feedback, current assessments yield latent results lacking depth and stakeholder involvement. Whilst knowing what could be measured to enhance HF insights, these techniques are underutilised and underdeveloped. Addressing the following questions is hence crucial for driving a shift in HFE.

1. What should be measured to understand the product interaction at hand?
2. What is this data's relevance to the scenario?
    - Is this data from a reliable source or supported by theory?
    - Are there interplaying factors?
    - If the interaction changes how does the data change?
3. How should data from different sources be synthesised?
4. How can I use the data to understand what features are detrimental or beneficial for users?
5. Can this information provided be used to make an informed decision on a product modification?

These questions act as a structural outline to the different steps of a revised data driven HFE approach. To develop an appropriate framework, analogies were pulled from other fields, in particular, condition-based monitoring. The OSA-CBM framework is a standard architecture aiming to foster a proactive approach to machine health, incorporating information from multi-modal data streams to achieve this (Mimosa, 2023). This information is utilised to make assessments of machine state, their current condition and what changes to the manufacturing procedure should be made, aiming to better incorporate design changes and improve interoperability of systems. The complexity of human behaviour requires adapting the comparison. Firstly, the behavioural complexity, along with the conclusions drawn from Section 2, demonstrate that a mixed-methods approach will be most effective when capturing insights as is often necessary when instigating archetypal changes in research methods (Abowitz and Toole, 2010). To do this effectively, teams with broader, interdisciplinary skill sets are required demonstrating, the need to include designers, users, experts, and other stakeholders at all stages. The developed framework, shown in Figure 3, aims to prompt exploration, questioning the appropriateness of posed questions, identifying additional factors, and addressing potential developmental challenges in implementation. Section 3.1 describes the considerations of the framework in further detail.

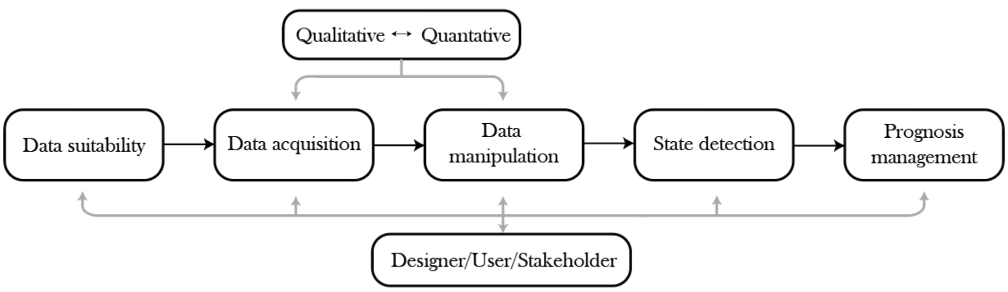

Figure 3. The data driven human factors framework

https://doi.org/10.1017/pds.2024.11 Published online by Cambridge University Press

3.1. Framework overview

Data suitability: Here, we must consider whether the direct quantitative measurement of a construct influencing product interaction is feasible and assess its importance. If not, a suitable proxy must be identified to formulate a hypothesis, based on established guidance where viable (ISO 6385:2016). This may evaluate the impact on motor skills, sensory capability, and processing skills, considering their overlap and quantitative capture feasibility in the given scenario. This is likely to be an iterative procedure, that persists as more information is revealed through synthesis. Challenges to implementation should be considered, including data privacy concerns and the potential for in-situ experimentation.

Data acquisition: This step looks to explore the methods by which a construct could be measured, and the level of abstraction they might hold to the construct (Jarecki et al., 2020). This involves exploring the compatibility of the data (Is this data from a reliable source or supported by theory?) the separability (Are there interplaying factors?) and testability (In the interaction changes, how does the measurement change?). To determine these, preliminary experimentation and a review of current techniques should be conducted. There are many potential technological prospects of techniques currently utilised in behavioural sciences and human computer interaction (HCI) that could be utilised in the context of product design as mentioned in Section 5.

Data manipulation: This stage aims to build a system so that higher level information can be inferred from data inputs, for example the creation of a multimodal analysis model or visual simulation. The use of multimodal data has shown to improve performance within classification tasks and triangulation of multiple methods has shown to increase experiment rigor, validity of results, reduce bias and error (Lee et al., 2015; Steinert and Jablokow, 2013). It is likely that synthesis of other measurement types will need to be completed, such as behavioural and subjective measurements.

State detection: This refers to the interpretation of system features, identifying what may be detrimental or beneficial to user groups. For complex data inputs, this may involve the creation of a learning network to find trends within the data presented or the need to define what an acceptable performance level may be. It's important to consider how much information is displayed back to designers and engineers, and what a useful level of insight will be.

Prognosis management: This stage looks at how we go about implementing changes based of what is detected in the previous stage. For example, how might a product look if it's dexterity demand were lowered? Throughout the operational stages, communication of information in the appropriate format, with the needed level of insight needed for learning or decision making should be considered.

4. Case studies

Within this section the descriptive value of the framework will be demonstrated and evaluated through case studies. The generalisability to different usage cases will be examined, leading to the identification of potential challenges to be discussed in Section 5, presented alongside technological prospects. The applicability of the framework within the context of the cast studies is displayed in Figure 4.

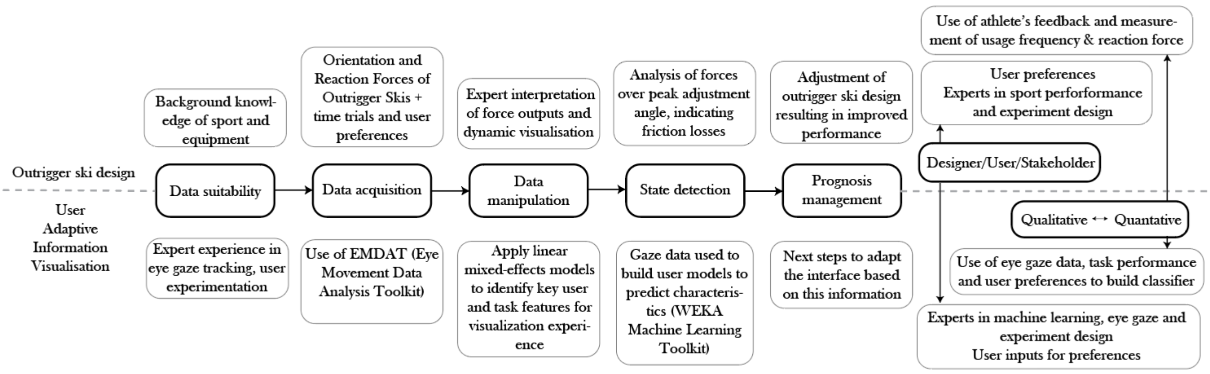

Figure 4. Illustration of case studies 1 & 2 within the context of the proposed framework

Case 1 - Outrigger ski equipment for paralympic alpine skiers: In Paralympic alpine skiing, several studies used data-driven methods to refine outrigger ski designs for better balance, speed control, and

https://doi.org/10.1017/pds.2024.11 Published online by Cambridge University Press

turning techniques. Modified outrigger skis, equipped to track orientation and force, revealed variations in athletes' techniques and identified efficiency losses. (Eikevåg et al., 2022; Silseth et al., 2021; Sletten et al., 2021). Similarly, adjustable outrigger skis, with varying angles of contact and length, were utilised to measure skier acceleration along a training track. Performance was then mapped against user preferences, finding that not only were the adjusted skis more comfortable for athlete's, but the performance improved by an average of 42% compared to the benchmark design.

Case 2: User-adaptive information visualisation: This project investigated what characteristics impact 2D information visualisation, utilising eye tracking data to monitor user attention patterns (Conati et al., 2015). The studies consisted of monitoring performance in graph-based tasks (simple bar, line, and radar charts), where users were asked to extract information from different information formats, equating performance with perceptual speed, visual and verbal working memory. It was found that users with low verbal working memory exhibited longer processing times, lower efficiency, and preference for text-based interfaces, suggesting that adaptive personalisation may consist of more graphical based interfaces, and vice versa for users with lower visual working memory. Additional work has been carried out to help identify when this support would be needed, suggesting that user confusion may be a possible indicator (Sims and Conati, 2020).

4.1. Evaluation of framework

As shown in Figure 4, both case studies showcase the distinct steps of the framework, providing insights into individual performances, allowing for more inclusive and improved design outcomes in case 1, with these outcomes yet to be determined in case 2. Both utilise simple data measurements to build up more complex understandings of user behaviour to adapt the interfaces as necessary, both expressing the value of real-time evaluation. The inclusion of HF specialists, experts in user experimentation, the interfaces and tools at hand and the users proved an essential element within both processes (See Challenge 2). Both examples exhibit different balancing of qualitative and quantitative data inputs and varying complexity of data streams. In case 2, the multi modal data streams mean state detection required deep learning, potentially limiting the transparency and interpretability of results. In both cases, while the inclusion of qualitative data is difficult to include, the current interpretation of these inputs is somewhat simplistic (Likert scales of preferences). These inputs could potentially remove details from user interpretations of the interfaces and raises concerns about integrating qualitative and quantitative data streams (See Challenge 1). Finally, while both cases state the intentions to realise the prognosis management stage, the implementation is relatively simplistic within case 1 and yet to be implemented within case 2. Further development of these projects, and knowledge about the technologies available to help implement this step is needed.

5. Prospect and challenges

Within this section, a non-exhaustive discussion of future technological prospects and challenges that are likely to arise during future implementation of the framework , as drawn out from the aforementioned case studies in Section 4, are discussed. Both are displayed in Figure 5, indicating the steps to which they are applicable.

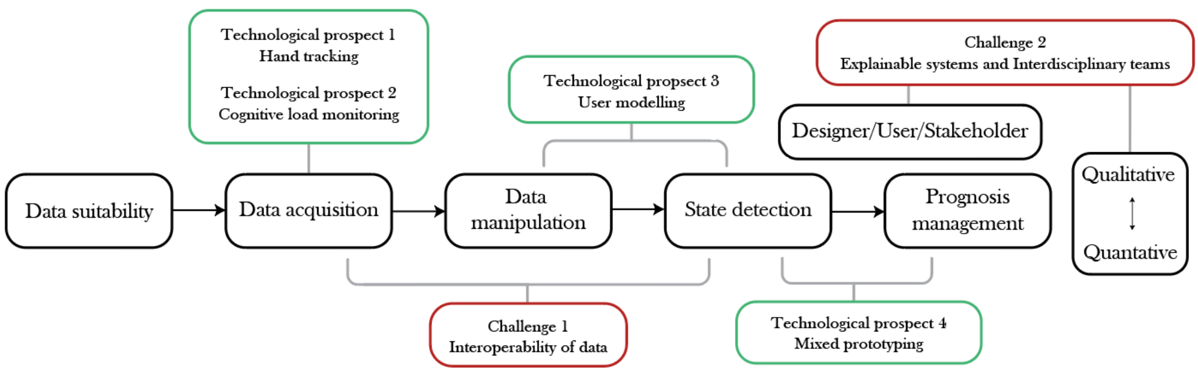

Figure 5. The technological prospects and challenges of the data driven HF framework

https://doi.org/10.1017/pds.2024.11 Published online by Cambridge University Press

Technological prospect 1 - Hand tracking: Gesture recognition and hand tracking are mature research areas, mainly aiming to advance how we interact with VR interfaces. Camera based systems such as Media Pipe[1] can provide hand landmark tracking in real time. In addition to this, wrist mounted gesture recognition systems are a promising development for the context of product interaction. These can detect hand position and even muscle activity without compromising a user's dexterity or being affected by occlusion. Common techniques include EMG (Electrical myography), arrays of infrared sensors, electrical impedance tomography (EIT), ultrasound and pressure sensors (Mcintosh, 2016).

Technological prospect 2 - Cognitive load monitoring: To evaluate human recognition of stimuli, several techniques have been developed over the last decade. As discussed in Section 4, eye gaze patterns have been utilised to recognise user cognitive capabilities as well as adapt to user's in real time for 2D interfaces (Steichen et al., 2013) and realisation of this for 3D interfaces could be realised using wearable eye tracking equipment[2]. Alternatively, portable neural imaging techniques, such as electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS) have shown to correlate brain activity to stimuli presence and the associated cognitive load, potentially helping to understand the intuitiveness of user steps (Dybvik et al., 2021).

Technological prospect 3 - User modelling: As demonstrated in Section 4, 2D and 3D visualisation of the modelling environment can help with further inspection of relevant parameters and determining those that have the biggest influence - enabled by the creation of deep learning toolkits such as WEKA[3]. The modelling of 3D environments and interaction tends to be bespoke, but the development of contact rich simulation modelling environments could help to address this. Myosuite utilises reinforcement learning and adapts hand grasps to manipulate an object with a given trajectory (Caggiano et al., 2022), considering factors such as muscle sarcopenia and fatigue. Implementation requires specialist knowledge, is computationally expensive and still requires further development to enable further dextrous operations.

Technological prospect 4 - Mixed prototyping: The incorporation of user feedback into the design cycle typically requires feedback of a few prototypes by users, adjusting based on feedback and iterating this procedure. The use of mixed-reality prototypes, created in a virtual space, streamlines the process, enabling quicker evaluation, model modification, and prototype creation, thus increasing the number of iterations within a given timeframe (Kent et al., 2021). This approach allows real-time alteration of the physical, functional, and psychological aspects of a product, facilitating systematic exploration of key interaction features (Cox et al., 2022). While mixed prototyping supports some product changes, re-imagining haptic feedback, especially in altering product interaction steps, remains challenging.

Challenge 1 - Interoperability of Data: Within several stages of the framework, the interpretation of multiple data streams in mixed formats is pivotal. The effectiveness of this will rely on the ability to interpret the data streams, which will rely on the expertise at hand, the computational resource available, data storage facilities, the data stream quality, applicability, and suitability to the problem amongst other factors. This also plays into the balancing of a mixed-method approach. As illustrated in Section 4, the quantification of human preferences could potentially remove the nuances, and the incorporation of qualitative feedback in a computational space is challenging. There is potential to involve text-based tools to enable creation of prototypes within a simulated space, such as DALL-E[4] or GPT Blender Add-ons[5], although tools that allow for alteration whilst still enable parametric design are limited.

Challenge 2 - Explainable systems and interdisciplinary teams: To maintain a human-in-the-loop approach, automated decisions and processes require explainability across stakeholders. The level of detail must be tailored to their needs: detailed insights for engineers and designers, and a clearer understanding of cost-benefit and high-level information for decision-makers and business owners. The development of explainable AI (XAI) systems in this context is pivotal, and the managing of over-reliance on AI systems must be carefully considered to ensure the sensible decisions are being made (Chen et al., 2023). Additionally, updated training of HF specialists and engineers to understand the

[1] Media Pipe: https://developers.google.com/mediapipe
[2] Tobii Pro Glasses 3: https://www.tobii.com/products/eye-trackers/wearables/tobii-pro-glasses-3
[3] WEKA: https://www.weka.io/
[4] DALL·E-3: https://openai.com/dall-e-3
[5] GPT Blender Add-on: https://www.blendermarket.com/products/blender-gpt

https://doi.org/10.1017/pds.2024.11 Published online by Cambridge University Press

potential limitations of these systems (Demirel et al., 2023) and the inclusion of machine learning expertise and electronic systems on HFE teams . This is intertwined with ensuring the efficacy of a mixed-method approach. Experts in the methods must be involved in product development to interpret and understand the best indicators, appropriate synthesis, and time scales.

6. Conclusions

In conclusion, the work presented advocates for a paradigm shift in HFE, moving towards a more data-driven and interdisciplinary approach. This proposition aims to address the need for faster product innovation and fostering of inclusive and user-centric outcomes. The proposed framework aims to integrate qualitative and quantitative methods in an age of automated decision making, addressing data suitability, data acquisition, data manipulation, state detection, and prognosis management. Case studies where this process is already being implemented in the early stages were summarised, showing the potential in both physical and digital systems. Throughout the framework, the need for expert involvement in both HFE, electronic systems and machine learning is essential to ensure robust data collection, decision making and incorporation of qualitative assessments. The assessment of this framework's advantages should be continuous, aiming to examine the ease with which it can be implemented alongside generative systems and simulation techniques, as well as the feasibility of integrating these mentioned technologies into a product design process.

References

Abowitz, D., Toole, T., 2010. Mixed Method Research: Fundamental Issues of Design, Validity, and Reliability in Construction Research. Journal of Construction Engineering and Management 136. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000026

Blanchonette, P., 2010. Jack Human Modelling Tool: A Review.

Caggiano, V., Wang, H., Durandau, G., Sartori, M., Kumar, V., 2022. MyoSuite -- A contact-rich simulation suite for musculoskeletal motor control. https://doi.org/10.48550/arXiv.2205.13600

Caine, M., Blair, K., Vasquez, M., 2012. Materials and technology in sport. Nature Mater 11, 655–658. https://doi.org/10.1038/nmat3382

Chen, V., Liao, Q.V., Wortman Vaughan, J., Bansal, G., 2023. Understanding the Role of Human Intuition on Reliance in Human-AI Decision-Making with Explanations. Proc. ACM Hum.-Comput. Interact. 7, 1–32. https://doi.org/10.1145/3610219

Conati, C., Carenini, G., Toker, D., Lallé, S., 2015. Towards user-adaptive information visualization, in: Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence, AAAI'15. AAAI Press, Austin, Texas, pp. 4100–4106.

Cox, C., Hicks, B., Gopsill, J., 2022. Improving Mixed-Reality Prototyping through a Classification and Characterisation of Fidelity. Proc. Des. Soc. 2, 353–362. https://doi.org/10.1017/pds.2022.37

Demirel, H.O., Goldstein, M.H., Li, X., Sha, Z., 2023. Human-Centered Generative Design Framework: An Early Design Framework to Support Concept Creation and Evaluation. International Journal of Human–Computer Interaction 1–12. https://doi.org/10.1080/10447318.2023.2171489

Dybvik, H., Erichsen, C., Steinert, M., 2021. Demonstrating the feasibility of multimodal neuroimaging data capture with wearable Electroencephalography + Functional Near-Infrared Spectroscopy (EEG+FNIRS) in situ. Proceedings of the Design Society 1, 901–910. https://doi.org/10.1017/pds.2021.90

Eikevåg, S.W., Grondahl, H., Sletten, H., Silseth, H., Steinert, M., 2022. Analysis of Kinetic and kinematic data from instrumented outrigger-skis of an elite Paralympic alpine skier: a pilot study, The Engineering of Sport. Perdue University. https://doi.org/10.5703/1288284317541

Fletcher, H., 2023. The principles of inclusive design: they include you.

Giacomin, J., 2015. What Is Human Centred Design? The Design Journal. https://doi.org/10.2752/175630614X14056185480186

HSE, 2023. Workstation assessments - Display screen equipment.

HSE, 2013. Workplace health, safety and welfare, L24.

HSE, 2007. Reducing error and influencing behaviour, HSG. HSE Books, Sudbury.

Imam, W., 2023. How to consider human factors in medical device design [WWW Document]. URL https://advisera.com/13485academy/blog/2017/09/28/considering-human-factors-in-medical-device-design/ (accessed 11.3.23).

Jarecki, J.B., Tan, J.H., Jenny, M.A., 2020. A framework for building cognitive process models. Psychon Bull Rev 27, 1218–1229. https://doi.org/10.3758/s13423-020-01747-2

https://doi.org/10.1017/pds.2024.11 Published online by Cambridge University Press

Joshi, M., Deshpande, V., 2019. A systematic review of comparative studies on ergonomic assessment techniques. International Journal of Industrial Ergonomics 74, 102865. https://doi.org/10.1016/j.ergon.2019.102865
Kanis, H., 1998. Usage centred research for everyday product design. Applied Ergonomics 29, 75–82. https://doi.org/10.1016/S0003-6870(97)00028-8
Kent, L., Snider, C., Gopsill, J., Hicks, B., 2021. Mixed reality in design prototyping: A systematic review. Design Studies 77, 101046. https://doi.org/10.1016/j.destud.2021.101046
Knott, D., 2001. The Place of TRIZ in a Holistic Design Methodology. Creativity and Innovation Management 10, 126–133. https://doi.org/10.1111/1467-8691.00213
Lee, M.-H., Fazli, S., Mehnert, J., Lee, S.-W., 2015. Subject-dependent classification for robust idle state detection using multi-modal neuroimaging and data-fusion techniques in BCI. Pattern Recognition 48, 2725–2737. https://doi.org/10.1016/j.patcog.2015.03.010
Maher, M.L., Poon, J., 1996. Modelling Design Exploration as Co-Evolution. https://doi.org/10.1111/j.1467-8667.1996.tb00323.x
Mcintosh, J., 2016. Exploring the practicality of wearable gesture recognition. University of Bristol.
Mimosa, 2023. Mimosa OSA-CBM [WWW Document]. URL https://www.mimosa.org/mimosa-osa-cbm/ (accessed 10.27.23).
Reason, J., 1990. Human Error. Cambridge University Press. https://doi.org/10.1017/CBO9781139062367
Scherer, C., Rose, C., 2023. 6 Indispensable Tools To Drive Effective User-Centered Design [WWW Document]. Med Device Online. URL https://www.meddeviceonline.com/doc/indispensable-tools-to-drive-effective-user-centered-design-0001 (accessed 11.17.23).
Silseth, H., Sletten, H.S., Grøndahl, H., Eikevåg, S.W., Steinert, M., 2021. Design of Experiment for Sports Equipment - Experimentally mapping the design space for Paralympic Alpine Outriggers. https://doi.org/10.1017/pds.2021.107
Sims, S.D., Conati, C., 2020. A Neural Architecture for Detecting User Confusion in Eye-tracking Data, in: Proceedings of the 2020 International Conference on Multimodal Interaction. Presented at the ICMI 20 : International Conference on Multimodal Interaction, ACM, Virtual Event Netherlands, pp. 15–23. https://doi.org/10.1145/3382507.3418828
Sletten, H.S., Eikevag, S.W., Silseth, H., Grondahl, H., Steinert, M., 2021. Force Orientation Measurement: Evaluating Ski Sport Dynamics. IEEE Sensors Journal. https://doi.org/10.1109/JSEN.2021.3124021
Steen, M., 2011. Tensions in human-centred design. CoDesign 7, 45–60. https://doi.org/10.1080/15710882.2011.563314
Steichen, B., Carenini, G., Conati, C., 2013. User-adaptive information visualization: using eye gaze data to infer visualization tasks and user cognitive abilities, in: Proceedings of the 2013 International Conference on Intelligent User Interfaces. ACM, pp. 317–328. https://doi.org/10.1145/2449396.2449439
Steinert, M., Jablokow, K., 2013. Triangulating front end engineering design activities with physiology data and psychological preferences: 19th International Conference on Engineering Design, ICED 2013. Proceedings of the 19th International Conference on Engineering Design 7 DS75-07, 109–118.
Thales Group, 2023. Human factors design [WWW Document]. Thales Group. URL https://www.thalesgroup.com/en/human-factors-design (accessed 11.16.23).
University of Cambridge, 2023. Inclusive Design Toolkit [WWW Document]. URL https://www.inclusivedesigntoolkit.com/usercapabilities/usercap.html (accessed 11.9.23).
Valdez, S., Seepersad, C., Kambampati, S., 2021. A Framework for Interactive Structural Design Exploration. Presented at the ASME 2021 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, American Society of Mechanical Engineers Digital Collection. https://doi.org/10.1115/DETC2021-71775
Whitefield, A., Wilson, F., Dowell, J., 1991. A framework for human factors evaluation. Behaviour & Information Technology 10, 65–79. https://doi.org/10.1080/01449299108924272
Wickens, C.D., Gordon, S.E., Liu, Y., 2002. An introduction to human factors engineering: Christopher D. Wickens; Sallie E. Gordon; Yili Liu, Nachdr. ed. Addison Wesley Longman, New York.
Wolf, A., Miehling, J., Wartzack, S., 2020. Challenges in interaction modelling with digital human models – A systematic literature review of interaction modelling approaches. Ergonomics 63. https://doi.org/10.1080/00140139.2020.1786606