# Towards an Ethical and Data Privacy Metrology for AI-Enriched Human-Centered XR Systems

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***Abstract*—This paper works towards an initial ontology of assessment techniques for building AI-enriched human-centered XR systems, denoted Intelligent Realities (IRs). Rather than connecting technologies, our work analyses the characteristics and requirements of IRs of being "human-centered" and creates an ontology of techniques to assess and measure these features. To achieve this, we use an approach based on *Formal Concept Analysis (FCA)* to establish a concept hierarchy from a set of critical concepts in the area and their properties. The novel concept defines a metrology, i.e., a set of concepts and units of measurement that can be used to shape the architecture of human-centered XR and metaverse systems. Our work focuses particularly on the ethical and privacy needs of system design.**

***Index Terms*—extended reality, intelligent realities, human-centered, metrology, ethics, data privacy**

## I. Introduction

Extended Reality (XR) or metaverse technologies, such as Augmented Reality (AR), Virtual Reality (VR), and Mixed Reality (MR), are increasingly becoming business opportunities, appearing as devices and viable applications. Besides focusing on visualization, XR systems require smarter information processing. Artificial Intelligence (AI) or Machine Learning (ML) techniques are essential for handling vast amounts of heterogeneous data in XR systems. AI should support users and enable transparent, trustful, safe, and understandable decision-making processes in the metaverse.

The above-outlined examples call for *human-centered* XR systems, i.e., metaverses designed around users and their needs rather than matching technologies. While the ambition of being a "human-centered" system is intuitive, its features and capabilities are hard to formulate. This paper objective is to answer the question of *how can an XR system be assessed as being human-centered?*. Thus, it aims to give insight into understanding "human-centered XR systems" with a primary focus on **ethical and data privacy** aspects.

Our contribution takes a novel approach. We attempt to describe a human-centered system by detailing measurable features rather than detailing specific technologies and mechanisms. This treatment of the problem will develop a *multi-feature metrology* for human-centered XR systems. We are inspired by the concept of *Formal Concept Analysis* (FCA) [1] for categorizing and relating assessment and measurement concepts for the main technology and concept areas, desired in such systems, and with the expected features of human-centered XR systems. These technology areas are denoted as *themes* and have been defined by the Swedish research project "HINTS – Human-Centered Intelligent Realities". Intelligent Realities (IRs) are an interpretation of the metaverse [2], which are highly immersive, ubiquitous, intelligent, and multi-user virtual spaces [3].

The rest of the paper is organized as follows. Section II presents requirements and assessment capabilities to be considered in AI-enriched human-centered XR systems. Section III briefly presents the HINTS project where these considerations have started to be applied. Section IV presents the methodology, and Section V discusses the initial results. Finally, Section VI concludes the work and proposes the next steps in enhancing the proposed ethical and data privacy metrology.

## II. Requirements and Assessment Capabilities

Assessing novel interaction modes in human-centered XR systems requires considering a variety of interwoven media and the context of multiple users. These needs point to ethical requirements, i.e., the ethical sourcing of information and data privacy needs, since information is exchanged between users or stakeholders, e.g., system operators. Combining these requirements is a new and complex task.

Furthermore, the concept of Eudaimonia aims to understand a human's well-being not as an "outcome or end state" but rather as a "process of fulfilling one's virtuous potentials and living as one was inherently intended to live" [4]. This concept expands the Quality of Experience (QoE) and Quality of User Experience (QUX) research due to its multifaceted nature (incl. emotion detection and emotion formation) and the assumption that it is a continuous process. QUX, in contrast, focuses on an instantaneous relationship between measurable User eXperience (UX) and network performance parameters.

AI-enriched human-centered XR systems will facilitate users' collaboration across multiple devices and environments. These intelligent systems require new robust, adaptive, and distributed AI/ML models. For example, Federated Learning (FL) is a promising solution for distributed ML frameworks [5], that trains the ML model at the edge and shares only model updates for building a global one. This allows for preserving data privacy, reducing the amount of data transferred and the

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energy consumed for communication. Although FL ensures significant data privacy, it is still vulnerable to attacks affecting aspects such as model performance, confidentiality, integrity, and availability of data [6], [7]. FL also raises issues relating to digital ethics, e.g., fairness w.r.t. the contributions of the involved parties or ownership of the model.

## III. Human-Centered Intelligent Realities (HINTS)

HINTS is an ongoing six-year research project funded by the Swedish Knowledge Foundation [3]. The project has identified five interrelated strategic technology and research areas of human-centered IRs, denoted *themes* and shown in Figure 1: a) novel experience assessment methodologies, b) novel environments and interaction techniques, c) visual analytics, d) adaptive and distributed AI, and e) networking support. These areas outline the variety and interdisciplinary nature of the methods and techniques required to design IRs.

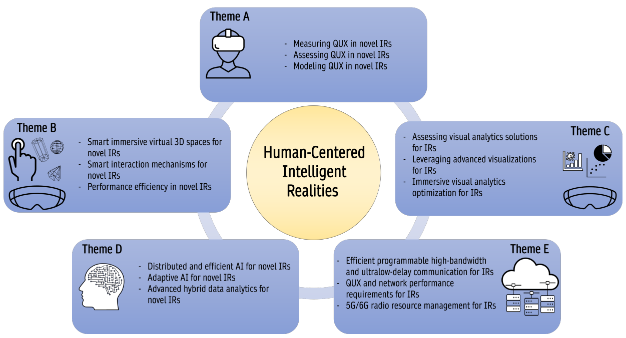


Fig. 1. Overview of the five research themes in HINTS [3].

### *Technology and Research Themes*

Theme A: It measures, assesses, and models QUX in IRs. These components enable creating a diverse experience assessment system, from controlled subjective tests to user studies. A combination of QoE and UX will build a framework to measure, assess, and model personalized QUX in novel IRs to discover human behavior and intent, solving challenges in immersive computing through a human-centered approach. To ensure that technical solutions are tailored to the needs of users, the QUX framework considers a range of human factors (HF). Among those HFs, ethical and data privacy considerations are needed when conducting user studies.

Theme B: This theme contributes to the visual component by delving into user-customized, intelligent 3D virtual spaces. Like user data getting customized across several domains, future XR-based spaces will also benefit from AI algorithms. Furthermore, Theme B envisions smart virtual spaces personalizing user interaction. With more affordable hardware like XR headsets, online shopping portals could be enriched for a more real experience to get the product feel before the purchase. Multiple users could also engage with each other in the virtual environment to make joint choices.

Theme C: Using advanced visual analytics techniques, Theme C bridges the gap between data analysis, visualization, and human analytical reasoning. It utilizes visualization techniques, including AI and ML algorithms, to integrate human cognition, perception abilities, and intelligence into the data-analysis process to obtain explainable results and discover complex patterns [8].

Theme D: The main focus is novel resource-efficient adaptive and distributed AI/ML approaches for IRs. New robust and evolving AI models that can be run on smart interactive devices with limited power and storage are studied. The aim is to develop novel hybrid immersive AI/ML-based analytical techniques to support reasoning and decision-making in complex data exploration scenarios. Human centricity is an important characteristic of such solutions. It highlights that AI/ML algorithms are part of a larger system consisting of humans, and they must be designed with this in mind [9], [10]. According to [11], human-centered AI's main components are aligned with ethics and human factors to ensure explainable, comprehensible, useful, and usable AI solutions and enhanced AI technology to reflect the depth characterized by human intelligence. Human-centered aspects of intelligent systems in the more narrow context of social responsibility usually refer to issues such as fairness, accountability, interpretability, and transparency. However, those can be considered in a much broader context, encompassing how data needed to train ML algorithms are collected and stored, how intelligent systems impact human work conditions and free time, how the earth's resources are used and from whom, etc.

Theme E: This theme concerns data networking, forwarding techniques, and hardware resource orchestrations and management for IRs. The theme considers novel network-compute continuums and fabrics, e.g., 5G's MEC [12]. Theme E is probably the least human-centered theme due to its resource focus. However, considering the strong relationship between network performance and QoE, e.g., [13], networking mechanisms significantly influence the UX and overarching concepts for user involvement, such as Eudaimonia [14]. In addition, the theme considers users' different interaction patterns. Network resource management is mainly needed for "1:1" communication where a single user consumes network media, e.g., provided by a server or by direct interaction with another single user. Routing, forwarding policies, and orchestration mechanisms gain importance in an IR if multiple users or compute entities collaborate, i.e., if they communicate an "N:M" pattern.

## IV. Methodology

This section introduces the foundation of the Formal Concept Analysis (FCA) method, which we partly used to build an ontology of metrology techniques for human-centered IRs.

### *A. Formal Concept Analysis*

The method that we suggest for the categorization and the construction of assessing AI-enriched human-centered features of XR systems is based on FCA, which is a method for data analysis, knowledge representation, and information management [1]. It allows the construction of a concept hierarchy (or formal ontology) from a collection of objects and their properties. Namely, a concept lattice is derived from a formal context consisting of a set of objects $O$, a set of attributes $A$, and a binary relation defined on the Cartesian product $O \times A$. The context is described as a table, the rows correspond to objects and the columns to attributes or properties, and a cross in a table cell means that "an object possesses a property". The concept lattice comprises concepts organized into a hierarchy by partial ordering. Intuitively, a concept is a pair $(X, Y)$, where $X \subseteq O$, $Y \subseteq A$, and $X$ is the maximal set of objects sharing the whole set of attributes in $Y$ and vice-versa.

### B. FCA-Based Ontology of Human-Centered IRs Metrology

To apply the FCA method, we must define and describe the sets $O$ of objects and $A$ of attributes using the considered methods and features. The set $O$ is filled by the assessment and measurement concepts related to each of the five themes, the five functional and technology areas in HINTS's human-centered IRs, cf. III. The elements of $O$ form the rows of Table I and are described in more detail in Section V for each theme. The attributes $A$ form the columns of the lattice in Table I and are also called features. We focus in our metrology on two categories of attributes, *data privacy* and *ethics*, and outline the important sub-features that we consider in these categories.

*1) Data Privacy:* The concept of *Data privacy* aims to empower users or citizens to decide who can process their data and for what purpose. It focuses on collecting, storing, retaining, and forwarding personal data within the applicable regulations and laws, such as GDPR [15] and HIPAA [16]. Data privacy and data security are closely related, but they are not interchangeable. Data security protects data against unauthorized access, loss, or corruption during the data lifecycle. Hence, data privacy is a subset of data security, which can not exist without data security. Many societies regard data privacy as a fundamental human right [17]. Privacy laws [15] consider the data processing steps and capabilities for user empowerment as features for privacy. Hence, we consider the privacy features of "data collection", "data storage", and "data retention", cf. [18].

*2) Ethics:* Research studies with physical or psychological impacts on people should be vetted according to Swedish law [19]. For example, cybersickness could be a side effect when using XR systems. It is more common for fully immersive VR systems [20]. In an ethical vetting process, the study design, risk-benefit, associated risks, risk mitigation and prevention, and what data needs to be gathered or used from existing sources need to be considered. Extra care regarding storage and access should be taken with sensitive personal information relating to ethnicity, political views, religion, health, sexuality, etc. Users should be informed before participating using an information letter. The letter should contain information about the study purpose, data collection and storage, requirements, task, length, risks, responsibilities, use of data, and the right to withdraw without giving a reason. Only by knowing this can users give informed consent before the study begins. How user recruitment is done is also important. Caution is needed when giving rewards or having some power relationship between the experimenter and the user since people might feel obligated to participate. It is also important that when users give informed consent, they are adults (over 18 in Sweden) who can assess the information properly. Special conditions apply when working with children or users with lower cognitive abilities [19].

## V. Initial Results and Validity

An initial metrology framework focused on ethics and data privacy for AI-enriched human-centered XR systems is proposed. This framework includes and discusses both objective and subjective assessments. The framework emphasizes the perspective of collaborative XR, where people might work together in novel ways. As one of the critical features of this framework is user-centered, the objective assessment in our framework is not only the system or network performance metrics such as accuracy, speed, and latency but also biometric measurements from the users when using XR systems. The framework highlights data privacy through data **Collection (P1)**, **Storage (P2)** and **Retention (P3)** [18]. The ethical considerations in the framework include a range of factors, including the impact on the individual and society as a whole for multi-user aspects. Ethical features we discussed are **Fairness (E1)**, **Discrimination (E2)**, **Justice (E3)**, **Bias (E4)**, **Reliability (E5)**, **Respect (E6)**, **Accountability (E7)** and **Interpretability (E8)** [21]. If one feature is related to the concept, an "$\times$" is marked in Table I.

Theme A: There are different ways of measuring the QUX in IRs, both subjective and objective. Traditional methods include subject testing of QoE and standard usability and UX questionnaires. Those measurements mainly work with human and societal factors such as efficiency, learnability, memorability, errors, satisfaction [22], attractiveness, dependability, stimulation, novelty [23], etc. Regarding data privacy and ethical factors, different methods are related to different features, see Table I. It is worth noting that simulator sickness can be a potential side effect among individuals using XR technology. As such, there is a need to measure and prevent this effect, which includes nausea, oculomotor, and disorientation [24]. It relates **E2:** Discrimination, **E4:** Bias, and **E6:** Respect in ethical factors.

Besides more traditional subjective ways, novel biometrical techniques such as Brain-Computer Interfaces (BCI), Eye Tracking (ET), Electroencephalogram (EEG), Electromyography (EMG), Galvanic Skin Response (GSR), and Heart Rate (HR) can provide a deeper understanding of XR system users. Biofeedback could quantify data such as visual attention (ET), emotional response (GSR), and level of stress (electrodermal activity, EDA) and show the users' intuitive feelings about XR systems and the impact of such applications. Due to the sensitive nature of biometric data and the potential misuse or abuse, it brings more challenges to ethical aspects [25]. Collecting, storing, and processing biometric data adhere to strict ethical guidelines. Such guidelines should prioritize protecting

| | Data Privacy | | | Ethics | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | P1 | P2 | P3 | E1 | E2 | E3 | E4 | E5 | E6 | E7 | E8 |
| Theme A | | | | | | | | | | | |
| Quality of Experience (QoE) | × | × | × | × | × | | | | | × | |
| User Experience (UX) | × | × | × | × | × | × | | | × | | |
| Usability | | | | | × | | | × | × | × | |
| Simulator sickness | | | | | × | | × | | × | | |
| User data | × | × | × | × | × | × | × | × | | × | × |
| Theme B | | | | | | | | | | | |
| User fulfillment experience | | | | × | × | × | × | × | | | |
| Feeling of connectivity | | | | × | × | | | × | | × | |
| Addressing special needs | | | | × | × | × | × | | × | | |
| User feedback | × | × | × | × | × | × | × | × | × | × | × |
| User data | × | × | × | × | × | × | × | × | | × | |
| Theme C | | | | | | | | | | | |
| User interaction | × | × | × | × | | × | × | × | | × | × |
| Data analysis | × | × | | × | × | × | × | × | | × | × |
| Usability | | | | × | | | | × | | × | × |
| User feedback | | | | × | | | | × | | × | × |
| Theme D | | | | | | | | | | | |
| Data analysis | × | × | × | | × | | × | | × | | × |
| Algorithm analysis | | × | × | × | | | × | × | × | × | × |
| Human analysis | × | | | | × | | × | | × | × | |
| Context analysis | × | × | | × | × | | × | × | | × | × |
| Outcome & user feedback analysis | | | | × | | | | × | | × | × |
| Contribution assessment in FL | | | | × | | × | | | × | × | |
| Theme E | | | | | | | | | | | |
| Latency | × | × | | × | | × | | × | | × | |
| Throughput | × | × | | × | | × | | × | | × | |
| Delay variation | × | × | | × | | × | | × | | | |
| Data locality | | × | × | | | | | | | × | |
| Timing of orchestration | | × | × | × | | × | | | × | × | |
| Access authorization | | | × | × | × | | | | × | × | |

TABLE I

A SAMPLE OF THE FORMAL CONTEXT CORRELATING ASSESSMENT CONCEPTS WITH HUMAN-CENTERED (DATA PRIVACY AND ETHICAL ASPECTS) FEATURES OF IRS. **P1**: COLLECTION, **P2:** STORAGE, **P3:** RETENTION, **E1:** FAIRNESS, **E2:** DISCRIMINATION, **E3:** JUSTICE, **E4:** BIAS, **E5:** RELIABILITY, **E6:** RESPECT, **E7:** ACCOUNTABILITY, **E8:** INTERPRETABILITY.

individual privacy rights, informed consent, transparency, accountability, and non-discrimination [21]. Therefore, the user data in Theme A are related to almost all the data privacy and ethical features in Table I.

Theme B: Several metrics could be employed while evaluating users' overall XR experience. Since the XR experience is a visual product of other factors working behind the scenes (for instance, network, AI, etc.), the parameters included for assessment might overlap; see also Table I. A key feature of all XR-based applications is the intended user immersion in the virtual environment [26]. A fluid and intuitive interaction framework is essential in shaping the overall interaction experience. A well-designed and developed virtual framework and interaction mechanism must still be supplemented by good peer-to-peer connectivity for a high-quality experience. Society is also moving towards a more inclusive approach. Ideally, developing related hardware and software should consider overall inclusiveness (ethnicity, gender, age, etc.). People with special needs are often accommodated by developing dedicated products or ones that can handle many scenarios.

Data privacy and ethics are connected to XR user environments. Remote virtually-based online environments are gaining popularity, thanks to the ubiquitous and inexpensive internet connectivity and affordable XR devices. This boom has led to multifold users joining such platforms. Many are naive or new users, like young children and senior citizens, potentially unaware of the potential data privacy risks. A large responsibility, therefore, lies on the software and hardware producers to educate the users of prevalent risks. This includes health-related issues that an individual might be exposed to while using XR (for instance, dizziness or disorientation). To this end, the discussion around this has started recently as the field itself has emerged [27], [28]. Additionally, user data storage, processing, and handling are important issues that all software (and even hardware) producers must be aware of. It is still a somewhat more established domain than the ethical dimension that arises with user usage and connectivity in XR platforms.

Theme C: Visual analytics systems play an important role in solving complex issues in diverse application domains, which support human decision-making. Due to their importance and the systems' influence in assisting humans in determining, e.g., fraud, patient sickness, and collision, privacy and ethical aspects concerning each domain should be considered. Hence, suitable evaluation methodologies are essential in enhancing the design and development of such systems.

Islam et al. [29] provide a recent systematic review of seven strategies for evaluating visual analytics systems, namely, 1) dashboard comparison, 2) insight-based evaluation, 3) log data analysis, 4) Likert scales, 5) qualitative and quantitative analysis, 6) Nielsen's heuristics, and 7) eye trackers. These strategies can be grouped under two main categories, i.e., System Factors (SF) and Human Factors (HF), where 1 to 3 belong to the SF, and 4 to 7 are considered HF. In addition, Battle et al. [30] discuss that visual analytics systems are primarily evaluated on how they support users in completing predefined high-level analysis goals. According to Thomas and Cook [31], visual analytics systems evaluation methods can be grouped into three different levels, namely component (e.g., interface design, interaction techniques, visual representation, and algorithm analysis), system (e.g., human information, discourse methods, and collaboration), and work environment (which includes both system and components).

With the focus on humans, the following metrics can be applied to measure various aspects of these levels, e.g., components can be evaluated based on efficiency, effectiveness, satisfaction, speed, scalability, and accuracy. At the same time, the system itself can be examined by considering utility and learnability aspects, and the work environment can be examined, w.r.t. user adoption, productivity, and satisfaction. Concerning these metrics, we consider user interaction, data analysis, usability, and user feedback about data privacy and ethics, as shown in Table I.

Theme D: Assessing human-centricity in AI systems is a complex task involving multi-view evaluation of different factors, e.g., social, ethical, environmental, technical, etc. This study considers assessment techniques related to AI systems' ethical and data privacy aspects (see Table I). The features usually considered in these categories are bias and fairness of AI systems, interpretability, transparency and explainability of the AI solutions, data origin, and collection [32]. Many of those are difficult to quantify, and no unified ways and measures are available for assessment.

The fairness of AI algorithms can be measured w.r.t. how equally the system treats different groups. Different data and model biases can be manifested, e.g., historical, representation, algorithmic, and evaluation. Detecting bias in AI systems requires a systematic approach that includes multiple steps and considerations of multiple perspectives. The popular approach to tackling AI bias and fairness is formalizing it as a mathematical constraint [33]. Equal Opportunity and Equality of Odds metrics from political theory can also be utilized to evaluate classification parity across groups. Data analysis techniques, such as visualization and quality assessment or descriptive statistics, can be used to identify data bias. One can apply algorithm testing and auditing or review code to detect bias in AI algorithms. Interviews, surveys, end-user involvement, and focus groups can also be used. Context and scenario analysis can be useful in assessing the impact of AI in different circumstances. However, a crucial step to ensure fairness and justice in FL requires objectively evaluating the involved parties' contributions to the shared model [34]. Preserving data privacy is another concern related to FL algorithms, e.g., it is challenging to achieve a good trade-off between privacy and personalization [35]. Various quantitative measures can be used to evaluate the effectiveness of data privacy controls. Such measures include analysis and assessment of data utility and data protection, i.e., their resistance to data privacy attacks and data compliance with applicable regulations and standards.

According to [36], interpretability is enabled through an AI system's explainability, transparency, intelligibility, and understandability, i.e., can be measured in those terms. In addition, it is usually realized through the user interacting with the system, enabling the user to understand the system's working modes better and improve its output. Solutions that explain the AI system results to the users contribute to human interpretation of predictions or classifications. Evaluating explainability is a complex task that requires considering both objective and subjective perspectives, and it may depend on the context and the user. Different methods can measure explainability, e.g., feature importance analysis, system outcome monitoring, and user feedback analysis.

Theme E: The relationship and impact of network mechanisms on the privacy and ethical features of IRs are mostly indirect. Typical network quality-of-service (QoS) measurements, such as latency, delay variation, and throughput, provide input for determining QoE, e.g., [37]. Since QoE is increasingly related to the overall Eudaimonic concept of user happiness [4], [14], such QoS measurements also give indirect insights into the degree of user satisfaction. The Eudaimonic concept extends the QoS/QoE relationship into categories of "hedonic" or "pragmatic" features such as "joy-of-use", "ease-of-use /utility", "meaningfulness/purpose-of-use", and "usefulness". These features are related, in our opinion, to the privacy features of "data collection" and "data storage". Hence, we provide specific "$\times$"s in the corresponding rows in Table I for these human-centered features and the QoS measurements. In addition, we consider that QoS measurements are similar, i.e., by the Eudaimonic relationship. For the ethical features of "fairness" or "justice", see "$\times$" in the rows of Table I.

Measurements and observation techniques at the infrastructure level and orchestration mechanisms can assess even the performance of complex multi-user/multi-entities scenarios, e.g., by synchronized measurement at arbitrary locations in the infrastructure. Even the locality data and the concise verification of data access (i.e., the degree of authentication and authorization of users or entities) can be assessed. These multi-location assessments relate to the privacy features of "data storage" and "data retention" and, in the ethics domain, indirectly, the feature of being "non-discriminative" due to authorized access.

Lastly, the timing accuracy of data orchestration, computing, and visualization entities impacts user satisfaction in IRs. This assessment is highly important for the "N:M" communication pattern. In addition, the features "data retention" (privacy domain), "non-discriminative", and "justice" (ethics domain) are impacted by orchestration mechanisms and the more current users who apply the IR concept.

The validity of the results is given in this work by providing pointers to state-of-the-art work or surveys for assessment techniques and human-centered features within each theme. However, the assessment techniques are not comprehensively outlined for each theme. This approach outlines multi-disciplinary techniques and diversity in the concept of "human-centered", even when only considering data privacy and ethics. The agglomeration of the theme-specific concepts provides a holistic understanding of the term “human-centered”. Our approach focuses on diversity, describing some possible assessment concepts per theme and, in turn, moving from a single assessment technique to multiple ones with relations by aiming at the same feature. Thus, the framework of Table I permits a more differentiated assessment of a system as being human-centered considering the technology and method areas of such systems, i.e., the themes.

## VI. Conclusions and Future Work

This paper proposes an initial ontology and relationship of assessment and measurement concepts with the desired features of human-centered IRs. It focuses on data privacy and ethics attributes. We formulated this relation by discussing assessment and measurement methods and how the observed objects relate to attributes of ethics and privacy for human-centered IRs. This builds into a context lattice inspired by the FCA method, i.e., Table I. The table connects observable objects with human-centered features for an initial metrology framework. The observable object can be applied to select and judge mechanisms or the overall architecture of IRs.

The framework is not yet comprehensive but enables the first interdisciplinary and inter-technology assessment of human-centered IRs. We hope our work sparks more research on both methodologies, how to build such metrology, and what assessment methods are needed for human and societal factors in IRs. We are committed to further developing this framework by incorporating more factors beyond ethics and data privacy, utilizing the terminology specified in the International Vocabulary of Metrology (VIM).

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## References

[1] B. Ganter, G. Stumme, and R. Wille, *Formal concept analysis: foundations and applications*. Springer, 2005, vol. 3626.
[2] H. Ning *et al.*, “A survey on the metaverse: The state-of-the-art, technologies, applications, and challenges,” *IEEE IoT Journal*, 2023.
[3] V. Sundstedt *et al.*, “HINTS: Human-Centered Intelligent Realities,” in *35th Annual Workshop of the Swedish Artificial Intelligence Society SAIS 2023*. Linköping University Electronic Press, 2023, pp. 9–17.
[4] R. Hursthouse and G. Pettigrove, “Virtue Ethics,” in *The Stanford Encyclopedia of Philosophy*, Fall 2023 ed., E. N. Zalta and U. Nodelman, Eds. Metaphysics Research Lab, Stanford University, 2023.
[5] B. McMahan and D. Ramage. (2017) Federated learning: Collaborative machine learning without centralized training data. [Online]. Available: https://research.google/blog/federated-learning-collaborative-machine-learning-without-centralized-training-data/
[6] T. Li *et al.*, “Federated learning: Challenges, methods, and future directions,” *IEEE signal proc. magazine*, vol. 37, no. 3, pp. 50–60, 2020.
[7] R. Gosselin *et al.*, “Privacy and security in federated learning: A survey,” *Applied Sciences*, vol. 12, no. 19, p. 9901, 2022.
[8] W. Cui, “Visual analytics: A comprehensive overview,” *IEEE access*, vol. 7, pp. 81 555–81 573, 2019.
[9] M. O. Riedl, “Human-centered AI and machine learning,” *Human behavior & emerging technologies*, vol. 1, no. 1, pp. 33–36, 2019.
[10] T. Capel and M. Brereton, “What is human-centered about human-centered AI? a map of the research landscape,” in *Proc. of the 2023 CHI conference on human factors in computing systems*, 2023, pp. 1–23.
[11] W. Xu, “Toward human-centered AI: a perspective from human-computer interaction,” *interactions*, vol. 26, no. 4, pp. 42–46, 2019.
[12] A. Filali, A. Abouaomar, S. Cherkaoui, A. Kobbane, and M. Guizani, “Multi-access edge computing: A survey,” *IEEE Access*, vol. 8, 2020.
[13] M. Alreshoodi and J. Woods, “Survey on QoE$\backslash$QoS correlation models formultimedia services,” *International Journal of Distributed and Parallel systems*, vol. 4, no. 3, pp. 53–72, 2013.
[14] S. Egger-Lampl, F. Hammer, and S. Möller, “Towards an integrated view on QoE and UX: adding the eudaimonic dimension,” *ACM SIGMultimedia Records*, vol. 10, no. 4, pp. 5–5, 2019.
[15] European Parliament and Council of the European Union. Regulation (EU) 2016/679 of the European Parliament and of the Council. [Online]. Available: https://data.europa.eu/eli/reg/2016/679/oj
[16] Centers for Medicare & Medicaid Services, “The Health Insurance Portability and Accountability Act of 1996 (HIPAA),” Online at http://www.cms.hhs.gov/hipaa/, 1996.
[17] European Parliament and Council of the European Union. Charter of the fundamental rights of the european union. [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:12012P/TXT
[18] S. Sharma, *Data privacy and GDPR handbook*. John Wiley & Sons, 2019.
[19] “Swedish ethical review authority,” accessed: 2024-05-08. [Online]. Available: https://etikprovningsmyndigheten.se/
[20] S. Martirosov, M. Bureš, and T. Zítka, “Cyber sickness in low-immersive, semi-immersive, and fully immersive virtual reality,” *Virtual Reality*, vol. 26, no. 1, pp. 15–32, 2022.
[21] “Ethics in research and good research practice,” accessed: 2024-05-08. [Online]. Available: https://www.vr.se/english/mandates/ethics/ethics-in-research.html
[22] J. Nielsen, *Usability engineering*. Morgan Kaufmann, 1994.
[23] B. Laugwitz, T. Held, and M. Schrepp, “Construction and evaluation of a user experience questionnaire,” in *4th Symp. of the Workgroup HCI and Usability Eng. of the Austrian Computer Soc., Graz, AT, Nov.*, 2008.
[24] R. S. Kennedy *et al.*, “Simulator sickness questionnaire: An enhanced method for quantifying simulator sickness,” *The international journal of aviation psychology*, vol. 3, no. 3, pp. 203–220, 1993.
[25] A. North-Samardzic, “Biometric technology and ethics: Beyond security applications,” *J. of Business Ethics*, vol. 167, no. 3, pp. 433–450, 2020.
[26] E. e. a. Raybourn, “Information design for XR immersive environments: Challenges and opportunities,” in *Virtual, Augmented and Mixed Reality. Multimodal Interaction, VAMR 2019, Orlando, FL, Jul.* Springer, 2019.
[27] M. Abraham *et al.*, “Implications of XR on privacy, security and behaviour: Insights from experts,” in *Nordic Human-Computer Interaction Conference*, 2022, pp. 1–12.
[28] S. Pahi and C. Schroeder, “Extended privacy for extended reality: XR technology has 99 problems and privacy is several of them,” *Notre Dame J. on Emerging Tech.*, vol. 4, p. 1, 2023.
[29] M. R. Islam *et al.*, “Strategies for evaluating visual analytics systems: A systematic review and new perspectives,” *Information Visualization*, vol. 23, no. 1, pp. 84–101, 2024.
[30] L. Battle *et al.*, “Evaluating visual data analysis systems: A discussion report,” in *Proceedings of the Workshop on Human-In-the-Loop Data Analytics*, 2018, pp. 1–6.
[31] K. A. Cook and J. J. Thomas, “Illuminating the path: The research and development agenda for visual analytics,” Pacific Northwest National Lab.(PNNL), Richland, WA (United States), Tech. Rep., 2005.
[32] A. Abdul *et al.*, “Trends and trajectories for explainable, accountable and intelligible systems: An HCI research agenda,” in *Proc. of 2018 CHI Conf. on Human Factors in Comp. Systems*, 2018.
[33] M. Buyl and T. De Bie, “Inherent limitations of AI fairness,” *Commun. ACM*, vol. 67, no. 2, p. 48–55, 2024.
[34] T. H. Rafi *et al.*, “Fairness and privacy preserving in federated learning: A survey,” *Information Fusion*, vol. 105, p. 102198, 2024.
[35] C. Meurisch and M. Mühlhäuser, “Data protection in AI services: A survey,” vol. 54, no. 2, 2021.
[36] E. Ventocilla *et al.*, “Towards a taxonomy for interpretable and interactive machine learning,” in *2nd Workshop on Explainable AI (XAI-18), 27th IJCAI, July 13-19, 2018, Stockholm, Sweden*, 2018, pp. 151–157.
[37] M. Fiedler, T. Hossfeld, and P. Tran-Gia, “A generic quantitative relationship between quality of experience and quality of service,” *IEEE Network*, vol. 24, no. 2, pp. 36–41, 2010.