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Towards Experience-Centered AI: A Framework for Integrating Lived Experience in Design and Development

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Abstract

Lived experiences fundamentally shape how individuals interact with AI systems, influencing perceptions of safety, trust, and usability. While prior research has focused on developing techniques to emulate human preferences, and proposed taxonomies to categorize risks (such as psychological harms and algorithmic biases), these efforts have provided limited systematic understanding of lived human experiences or actionable strategies for embedding them meaningfully into the AI development life-cycle. This work proposes a framework for *meaningfully* integrating lived experience into the design and evaluation of AI systems. We synthesize interdisciplinary literature across lived experience philosophy, human-centered design, and human-AI interaction, arguing that centering lived experience can lead to models that more accurately reflect the retrospective, emotional, and contextual dimensions of human cognition. Drawing from a wide body of work across psychology, education, healthcare, and social policy, we present a targeted taxonomy of lived experiences with specific applicability to AI systems. To ground our framework, we examine three application domains— (i) education, (ii) healthcare, and (iii) cultural alignment—illustrating how lived experience informs user goals, system expectations, and ethical considerations in each context. We further incorporate insights from AI system operators and human-AI partnerships to highlight challenges in responsibility allocation, mental model calibration, and long-term system adaptation. We conclude with actionable recommendations for developing experience-centered AI systems that are not only technically robust but also empathetic, context-aware, and aligned with human realities. This work offers a foundation for future research that bridges technical development with the lived experiences of those impacted by AI systems.

1 Introduction

Lived experience signifies the *the view from inside* (Casey 2023) in that it often captures the subjects' interpretation of the object. Lived experience differs based on whether reality is perceived as distinctive values or continuously meaningful in the relation of *object* and *subject*. Contrasting this, within our context of human-computer interaction (HCI) literature, experience is postulated as authentic and having universal qualities (Kruks 2014). The positioning of *experience* as *universal* creates the need for evidence-based truth or belief of self-evidence to be reliable. This can be harmful as evidence-based truth captures singular realities while lived experiences are multifaceted in nature. Thus, it becomes important to contextualize, structure and define lived-experiences. A framework evaluating the role of human lived experiences in AI would provide a comprehensive method for incorporating these experiences into AI design. Examining lived experiences can inform strategies for creating AI agents that set clearer expectations, provide empathetic responses, and adapt to user contexts. For example, AI systems should be designed to probe user goals and intents to personalize interactions *meaningfully*.

Human-AI value alignment has been a focal point of ongoing and widespread deliberation at both AI and HCI venues (Shen et al. 2024b,a; Turchin 2019; Terry et al. 2023; van der Maden, Lomas, and Hekkert 2023; Chandra et al. 2025a). The diversity of human values across cultures presents challenge for achieving meaningful AI alignment. Prior work has covered critical discourse and provides theoretical frameworks for value alignment in the context of generative AI in the workforce, with a focus on community and organizational values (Shen et al. 2024b). Aligning AI systems with nuanced, context-specific human experiences can lead to more equitable, inclusive, and effective outcomes in human-AI interaction (Terry et al. 2023). Unlike existing approaches that rely heavily on psychological taxonomies or quantitative surveys, this work emphasizes the integration of lived experiences throughout the AI development life cycle, not as a static checklist but as a dynamic and continuous consideration (van der Maden, Lomas, and Hekkert 2023; Forum 2024). Our paper addresses key limitations in prior alignment frameworks by centering lived experience — defined as retrospective, emotional, and contextual— as foundational to AI system design and evaluation (Table 1). Drawing from literature in philosophy, human-centered design, and HCI, **the LEAF framework** (**L**ived **E**xperience Centered **AI** **F**ramework) situates lived experience as critical to understanding user interaction, trust, and well-being, particularly in domain-specific contexts such as education,

Framework/Paper	Core Approach	Value Basis	Methodology	Unique Features
Fundamental Value Alignment (Shen et al. 2024b)	Psychological value taxonomy	Schwartz Theory, 49 values	Surveys, value measurement	Systematic value checklist, context-aware scenarios
AI Policy Alignment (Forum 2024)	Policy & guidelines	Societal/shared values	Framework review	Global, policy-oriented
Measuring Human-AI Alignment (Norhashim and Hahn 2024)	Empirical measurement	Human values (surveyed)	Quantitative analysis	Focus on LLMs, misalignment quantification
Bi-Directional Alignment (Shen et al. 2024a)	Human-centered, bidirectional	Human/AI adaptation	Systematic review	Mutual adaptation emphasis
Human Well-being (van der Maden, Lomas, and Hekkert 2023)	Wellbeing, cybernetic theory	Eudaimonic wellbeing	Human-centered design	Community-led, feedback loops
Our Paper (LEAF)	Lived experience centered	Contextual, emotional, retrospective	Interdisciplinary synthesis, domain-specific case studies	Embeds lived experience in lifecycle, empathy, responsibility allocation

Table 1: **Comprehensive Overview of Human-AI Value Alignment Frameworks**, including a comparison of our lived experience-centered approach with prior work.

healthcare, and cultural alignment. By doing so, it highlights the need for empathetic, context-aware AI systems that reflect and respond to the realities of those they impact.

A systematic exploration of lived experiences in AI also necessitates methodological pluralism. A truly human-centered AI approach must consider subjective experiences, embodied intelligence, and first-person perspectives (Bingley et al. 2023; Capel and Brereton 2023). This involves recognizing the primacy of lived experience in understanding human cognition and integrating multi-modal sensory communication into AI systems (Rix-Lièvre, Cahour, and Guibourdenche 2024; Dieumegard et al. 2021). Memory and retrospective experience play a critical role in how humans navigate the world, and AI models should strive to mirror these aspects more effectively (Howard 2018; Steinhardt 2019; Chiorri and Vannucci 2024; Kahneman and Riis 2005). In this work, we present **the LEAF** that emphasizes the integration of human lived experiences throughout the AI development life cycle, guiding their incorporation into both design and evaluation processes.

This paper positions lived experience as a foundational lens for aligning AI systems with the nuanced realities of human users, focusing on design, evaluation, and deployment processes. We first define lived experience and explore its relevance in shaping human–AI interactions, especially in high-stakes and everyday contexts. We then introduce a conceptual framework structured around four key dimensions of lived experience: (i) sense of self, (ii) health, (iii) social and cultural identity, and (iv) learning. Building on this framework, we identify specific stages within the AI development pipeline where lived experience can be meaningfully integrated and offer actionable design recommendations to support the inclusion of diverse experiential perspectives. Through real-world case studies in domains such as education, healthcare, and religion, we demonstrate how attention to lived experience can inform more inclusive, empathetic, and context-aware AI systems. Thus, our work contributes a structured approach for embedding lived experience into the lifecycle of AI systems, with the goal of guiding more responsible and socially grounded AI practice.

2 Facets of Lived Experiences

The concept of lived experiences goes back as late nineteenth century (Casey 2023). Although scientific research has shifted over time—from being primarily observational in the 18th and 19th centuries to becoming more experimental and data-driven today, there is a renewed recognition of the value of lived experience. It can be traced, historically, to documentation of personal or observational accounts have led to both societal and scientific progress (Scott 1991). This section explicates the definitions, dimensions and importance of lived experience relevant to the LEAF framework.

2.1 What Do We Mean by Lived Experiences – Taxonomy of Lived Experiences

The Oxford English Dictionary defines “***Lived Experience***” as“*Personal knowledge about the world gained through direct, first-hand involvement in everyday events rather than through representations constructed by other people. It may also refer to knowledge of people gained from direct face-to-face interaction rather than through a technological medium*”(Dictionary 2025). Likewise, the concept of lived experience has been studied across disciplines such as psychology, philosophy, sociology, and clinical science, serving as an important lens to deepen our understanding of human experiences and realities. The term *lived experience* was first popularized within the field of philosophy with the lens of objectivity (Bunnin and Yu 2008; Casey 2023), particularly through the work of Wilhelm Dilthey, to represent individual’s embodied, first-person, pre-reflective experience of themselves and their world. Within Philosophy, Phenomenology specifically focused on lived experiences and aimed to understand the nature of conscious experiences and the significance of phenomena from a first-person perspective (Smith 2018).

As articulated in Heidegger’s philosophy (Heidegger et al. 1962), lived experience is rooted in the ontological structure of human existence, conceptualized through the notion of Dasein, or “being-in-the-world”. Rather than viewing individuals as isolated observers, Heidegger emphasizes that human beings are always already situated within a particular social, historical, and relational context (Korteling et al. 2021). Lived experience, in this view, is

Figure 1: Dimensions of lived experience drawn from cross-disciplinary literature in psychology, artificial intelligence, healthcare, and HCI. These dimensions serve as interpretive guides for situating lived experience within sociotechnical systems.

shaped through the continuous and intimate interaction between self and world (Miles et al. 2013). It is not merely about what is observed, but how being is experienced from within—contextually, temporally, and meaningfully (Korteling et al. 2021). Hermeneutic phenomenology, drawn from Heidegger's ideas, therefore seeks to uncover the implicit meanings embedded in everyday life, interpreting these meanings as expressions of one's existence in the world (Spiegelberg 2012).

Within sociology, the concept of lived experience encompasses individual perceptions, interpretations, and emotional responses to life events that are often shaped by social, cultural and historical factors involving interactions with others (Mackee 2024). Past research has explored various facets of lived experience ranging from personal experiences, work-related experiences, and social relationships. Below, we highlight examples from AI ethics research and related fields that illustrate how lived experiences have been centered in the design and development of AI systems.

Portway and Johnson (2005) conducted a study understanding experiences of young adults with Asperger's syndrome within the society. In another study, researchers focused on understanding the association between well-being, sense of belonging, connectedness to community (Haim-Litevsky, Komemi, and Lipskaya-Velikovsky 2023). They found that sense of belonging was associated with increased well-being. Feminist theory has been a prominent framework for examining how gender and social relations shape the lived experiences of women and other marginalized gender groups (Garko 1999; Patterson et al. 2016). In addition to gender identity, cultural background has also been recognized as an important factor in shaping individual experiences (Pufall-Jones and Mistry 2010).

In psychology and clinical science, lived experience has been recognized as a key component towards understanding patient well-being. Past works have explored ways to integrate lived-experience perspectives of patients in mental healthcare (Happell and Roper 2007; Walsh and Boyle 2009). Past research has also shown that integrating lived experiences can lead to higher-quality research outcomes, better acceptance of treatment procedures and increased patient outcomes (Brett et al. 2014; Goodare and Lockwood 1999; Beames et al. 2021). Other works have explored ways to integrate patient's lived experience into the clinical process pipeline. For instance, Otado et al. (2015) examined strategies for overcoming barriers towards recruiting individuals from African American communities. Such strategies included providing informational sessions and disseminating newsletters about study outcomes.

Lived experience has also been valued in educational settings for both educators and learners. Past works have shown that integrating lived experience of end consumers within health profession education leads to more empathetic and nuanced understanding of health and illness among health students and professionals (Soon et al. 2020). Matu and Perez-Johnston (2024) found that implementing culturally relevant pedagogy that encompassed diverse lived experiences fosters a culturally diverse learning environment, leading to enhanced cultural competence, critical thinking, global citizenship and academic achievement.

Lived experiences have also been explicated as *expertise*, with international consensus, especially in health, design and technologies (Muchamore, Karanikolas, and Gooding 2024; Chandra et al. 2025a,b). Likewise, scholars in personal informatics have emphasized the importance of incorporating lived experiences and subjectivity into data-centric systems that, as they note, *"attend to people's subjective perspectives on personal informatics*" (Cosley et al. 2017). This comes from the idea that, the focus on rational self-improvement in personal informatics often overlooks the lived, emotional, and evolving experiences people have with tracking technologies, which can exclude some users and even cause harm when misaligned with their actual needs (Rooksby et al. 2014; Cosley et al. 2017).

While the concept of lived experience has been extensively examined within the aforementioned disciplines, it remains widely misunderstood and largely overlooked in AI research, particularly within natural language processing (Girju 2023). Past works have also highlighted the distinction between human-intelligence from artificial intelligence (AI), making it important to understand the role of lived experience within AI (Olivier 2017). Hence, in this work, we examine what constitutes the concept of lived experience specifically in the context of AI, and how it can inform the development and design of more user-centered AI systems. For the purposes of this framework, we define *"user"* to include both the end consumer of the technology and the facilitator who leverages it. For example, in the case of an AI chatbot used in a healthcare setting, both the care provider using the chatbot and the patient interacting with it are considered users.

2.2 Importance of Lived Experience Within Technology Design

AI development has traditionally treated users as abstract data subjects, reducing their behavior to patterns that can be learned and optimized. As Ziewitz and Singh (2021) argue, the lived experience of data subjects remains deeply embedded in their life worlds, and cannot be fully understood through data alone [1]. If AI systems are to be trustworthy, fair, and responsive to the people who use them and more importantly the people they affect, their development must incorporate not only technical metrics but also the grounded, subjective knowledge that individuals bring (Freiman 2023; Adeofe 1995). Thus, designing with lived experience does not replace data-driven methods (Markham and Pereira 2019), but complements them as they have the potential of exposing blind spots (Frank, Gleiser, and Thompson 2024), surfacing harms (Scheuerman, Branham, and Hamidi 2018), and foregrounding the perspectives of those often marginalized in the design process. It is important to note here that while marginalized communities face a higher risk of erasure (Cantley 2025), this framework is guided towards all communities. Mentions of marginalized communities, henceforth, are as an illustrative example that should extend to other communities as well. Likewise, AI ethicists, have often explicated, that lived experiences be accounted for when building systems, and have attempted to do so, especially in systems and technologies in social and public sectors (See for example, (Birhane et al. 2022)).

In recent times, as AI is increasingly repurposed and appropriated for knowledge generation and sharing, lived experience has gained importance due to the shifting epistemologies introduced by technologies such as large language models (Mugleston et al. 2025). As these systems increasingly mediate knowledge production and dissemination, they risk flattening culturally specific ways of knowing (Amershi 2020). Likewise, it is important to note that knowledge is not merely abstract or universal – it is often rooted in lived, situated experience. Expertise emerges through embodied engagement with the world, not just formal instruction (Casey 2023). AI systems that ignore these dynamics, risk distorting or disregarding the very contexts that lend meaning to knowledge.

We now turn to a more in-depth examination of how these conceptual differences manifest in the design of artificially intelligent systems. A recurring critique of lived experience as a construct is its perceived lack of scientific rigor and its limited applicability to empirical, real-world contexts (Maggs-Rapport 2001). This critique highlights a broader epistemological divide between experiential knowledge and traditional scientific paradigms (Allison and Pomeroy 2000). In this paper, we aim position ourselves within that gap, also attempting to bridge it by situating lived experience within a scientifically grounded framework. Given the inherently subjective and deeply embedded nature of these issues within human experience, we argue that integrating lived experiences into the design and evaluation of AI systems can offer critical insights and serve as a valuable strategy for mitigating these harms.

[1]https://www.mhc.wa.gov.au/our-initiatives/our-projects/lived-experience-(peer)-workforce-project

2.3 Dimensions of Lived Experiences

Building on prior research examining bias and harm in AI systems (Shelby et al. 2023), we offer a lens for organizing and understanding how lived experiences manifest in relation to AI design and use. Figure 1 presents a visual presentation of the organization. Rather than presenting rigid or discrete categories, we identify seven interrelated thematic dimensions that commonly surface in the literature. These dimensions—drawn from cross-disciplinary frameworks in psychology, AI, healthcare, and HCI, serve as interpretive guides for situating lived experience within sociotechnical systems. In the sections that follow, we outline each dimension with illustrative examples, recognizing that they are fluid, overlapping, and context-dependent rather than mutually exclusive or exhaustive.

- **Sense of Self** : Among the most difficult dimensions of lived experience to quantify are those rooted in personal, introspective reflection (Schwarz and Clore 1996). These experiences often inform individual consumption patterns and preferences, shaped significantly by reflective processes. Reflective experiences capture the retrospective interpretation of events, rather than their immediate, in-the-moment perception (Kahneman and Riis 2005). Such reflection frequently leads to reflective learning, which plays a crucial role in shaping how lived experiences evolve for individuals (Boud, Keogh, and Walker 2013). Intuition and tacit knowledge are central to this process, aligning with Schön's theory of reflective practice, which emphasizes learning through thoughtful engagement with one's actions and experiences (Schön 1979). Closely tied to reflective experience is the concept of metacognition—the awareness and regulation of one's cognitive processes (Schraw and Dennison 1994). Predominantly studied within learning sciences, metacognitive awareness enables individuals to evaluate and adapt their learning strategies (Wade and Reynolds 1989). Interaction with AI systems, particularly those used in educational settings, can disrupt existing mental models of learning by introducing alternative paths of information navigation and knowledge construction (Do et al. 2024). Emerging research on the use of AI in learning contexts illustrates how these systems influence metacognitive patterns and learning behaviors (Fan et al. 2025). When considering lived experiences that inform one's sense of self, it is important to account for the complex and often deeply personal influence of prior traumatic experiences. These histories can shape emotional responses and engagement with AI technologies in ways that are not easily predicted or generalized. Such instances require nuanced, context-sensitive approaches that extend beyond standard user experience models and design practices (Siddals, Torous, and Coxon 2024).
- **Health** : Contexts in health are heavily impacted by lived experiences. As conversational agents become more common in mental health contexts—often valued for the

perceived privacy, nonjudgmental interactions, and emotional safety they offer users (Lee et al. 2025)– it is essential to integrate the lived experiences of health practitioners into the design and governance of such systems. These practitioners possess expertise through years of experiences in navigating complex emotional scenarios, which current AI systems often lack. Research has shown that users may turn to general-purpose AI during moments of psychological distress (Song et al. 2024), sometimes appreciating the model's perceived neutrality, even when cultural awareness is absent. However, such use cases can be unpredictable and highlight the limitations of designing for narrowly anticipated needs. Health practitioners' experiential knowledge is therefore crucial not only for identifying risk but also for understanding edge cases and contradictions that may otherwise go unrecognized. Their involvement can help ensure that AI tools are contextually appropriate and safe, especially in high-stakes scenarios (Olawade et al. 2024). In medical consultation, rising healthcare costs and limited access to care have fueled reliance on AI tools. Even before the AI boom, platforms like WebMD reflected a public need for alternative guidance (Staff 2016). Today, conversational medical agents continue this trend, but often fail to reflect the nuanced knowledge of practitioners. For instance, LLMs struggle to address adverse psychiatric drug reactions and rarely account for trauma or disability contexts (Chandra et al. 2025b). Without grounding in lived practitioner and patient experience, such systems risk offering decontextualized and potentially harmful advice.

- **Social and Cultural** : We intentionally address social and cultural contexts together to emphasize their intertwined nature across most lived experience scenarios. This entanglement often lends cultural experiences a perceived authenticity—one that may be accepted uncritically rather than subjected to reflective scrutiny. Consequently, when researchers draw on individuals' experiences, there is a risk of mistaking these accounts as direct, unmediated sources of truth, rather than recognizing them as shaped by complex socio-cultural frameworks (McIntosh and Wright 2019). As introduced in the section above, foundational feminist theorists such as Simone de Beauvoir (Kruks 1992) and Edith Stein (Feldhay Brenner 1994) emphasized the importance of recognizing sexual difference as integral to women's embodied experience and consciousness. Beauvoir, in particular, drew on Husserl's distinction between the body as an object of detached observation (Körper) and the body as it is subjectively lived and experienced (Leib) (Coolen 2014). Thus, gender identities and lived experiences are deeply influenced by social, geographic, and political contexts, which in turn shape how individuals engage with AI systems (Armutat, Wattenberg, and Mauritz 2024). These contextual differences contribute to varied human behaviors and perceptions, especially regarding technology adoption and trust. Likewise, this becomes an important example of how social and cultural nuances of lived experience have significant implications, affecting outcomes such as workplace hiring, representation in socio-technical domains, and the equitable deployment of AI technologies (An et al. 2024; O'Connor and Liu 2024).
- **Learning** : One of our greatest human capacities is the ability to learn from both personal and others' experiences. Yet this form of knowledge is often undervalued, as rational prioritizing external sources of information over lived human experience (Farrell 2020). Students' mental models of learning, informed by both personal experience and educational theory (Jonassen and Henning 1999), shape how they engage with instruction. Replacing human educators with AI systems risks overlooking the contextual expertise instructors develop over years of practice (Luckin and Holmes 2016). Much learning occurs beyond formal instruction—for example, through peer tutoring fostered by classroom relationships (Selwyn 2019). For example, in Giles' study (Giles, Smythe, and Spence 2012), grounded in Heideggerian and Gadamerian philosophy (Magrini 2011), the authors show that teacher–student relationships are foundational to the educational experience yet often overlooked.Additionally, instructors contribute by integrating diverse student backgrounds and building classroom resilience, offering a depth of lived experience that current AI systems struggle to replicate.

Given the discussion above, it is also important to talk about dimensions that are complex. As previously discussed, lived experiences play a crucial role in facilitating this alignment. A key facet of both cultural context and personal identity is moral alignment (Naous et al. 2023). While substantial work has been undertaken to establish alignment with human values (Han et al. 2022; Frempong and Kadam 2024)—resulting in the development of alignment scales and frameworks—moral alignment remains particularly challenging. This difficulty stems from the divergent and often conflicting values that arise from personal, community, cultural, national, and other contextual layers (Markus and Lin 1999). Such complexity resists straightforward categorization, as moral orientations are not easily captured by static typologies. In this regard, lived experiences offer critical insights that can inform and enrich the design of AI systems.

3 Lived Experience Framework Within the AI Development Pipeline

Incorporating lived experiences into AI development workflows presents different opportunities to rethink the design techniques where technology is used for human good, especially in computer science, biomedical, humanities, and social sciences. We can include lived experience at any stage of designing, developing, and deploying AI systems, but its role and impact differ depending on the phase and the application. To this end we propose **Lived Experience Centered AI Framework (LEAF)**. It ensures that AI models are grounded in real-world concerns, especially those of communities often marginalized in technical design processes. This creates the possibility for co-creative design, where

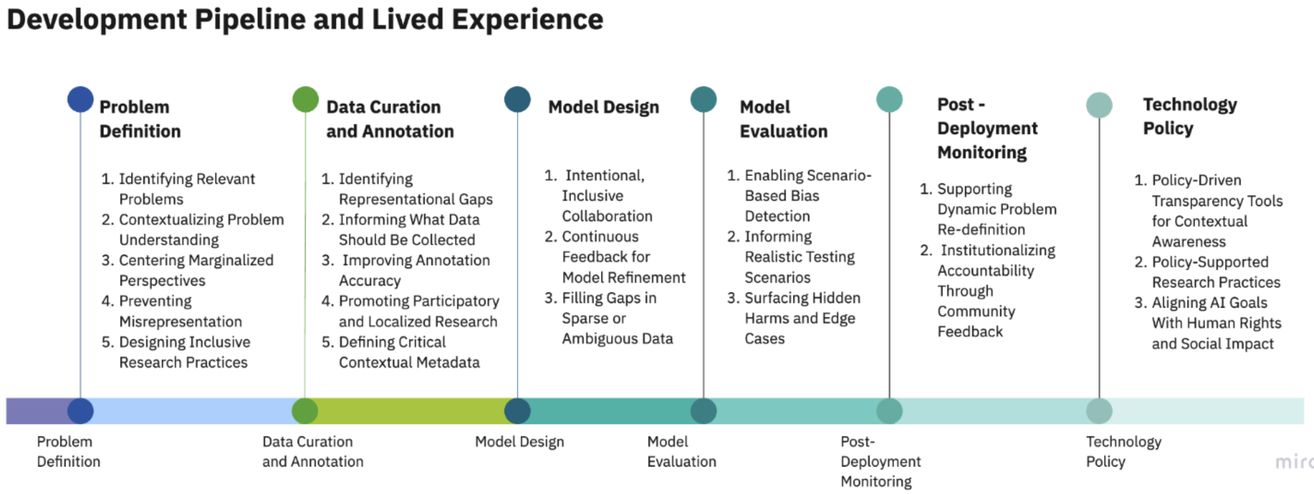

Figure 2: Outline of a typical AI development pipeline and how the LEAF can be leveraged to incorporate the human lived experience at each stage. Each stage name is highlighted **bold** (eg: Model Design), followed by processes recommended in the LEAF to meaningfully incorporating human lived experiences.

tools reflect technical feasibility and cultural and social relevance. In this section, we have explained how we can integrate lived experiences throughout the research life cycle. Figure 2 presents a visual representation of the LEAF.

3.1 Problem Definition

Lived experiences can play a critical role in shaping the early stages of AI development, particularly in defining the problem space. Rather than relying on technical abstractions or dominant normative frameworks, incorporating lived experience brings attention to how people actually encounter and are affected by a given issue. This perspective helps uncover situational nuances that are often overlooked in top-down design approaches (Ajjawi et al. 2024). The “gulf of execution”, as described by Norman (Norman 1988), highlights the disconnect between a user’s intentions and the system’s affordances or interface. This gulf can be significantly widened when systems are not designed with attention to users’ contextual realities. Lived experience—encompassing people’s tacit knowledge (Mascitelli 2000), cultural contexts (Ginn 2016), and everyday practices (Ajjawi et al. 2024) — helps bridge this gap by aligning the psychological language of users with the operational language of the system. When excluded from the early design process, systems risk embedding the assumptions of developers rather than reflecting the diverse needs of actual users, especially those from marginalized communities.

For instance, in natural language processing tools aimed at detecting depression or anxiety on social media, researchers have found that standard models often misclassify language used by LGBTQ+ or neurodivergent users, whose expressions of distress deviate from dominant linguistic norms (May et al. 2019). Similarly, predictive policing tools such as PredPol, developed without engagement from overpoliced communities, reproduced systemic bias and flawed assumptions about criminal behavior (Mugari and Obioha 2021). These failures underscore the importance of integrating lived experience at the problem-definition stage. Participatory approaches—such as co-design workshops or speculative design sessions—can facilitate this integration, grounding early prototypes in the realities of those most affected. For example, Brogden et al. (Brogden et al. 2024) reflect on the value of including young individuals with lived mental health experiences in the design of digital health tools, showing how such engagement improves relevance and trust.

3.2 Data Curation and Annotation

During data curation, lived experience helps identify representational gaps, and guides more inclusive annotation practices. We can include lived experience to understand what data should be included, how it should be labeled, and what contextual metadata is critical for humanities during the data sourcing, selection, labeling, and validation stages of AI development to mitigate bias. For example, medical datasets are often male-dominated or exclude non-binary individuals, leading to diagnostic tools that fail to detect symptoms in women or gender-diverse patients(Obermeyer et al. 2019). We need a community-led data annotation process because annotators without relevant lived experience may mislabel content, especially when it involves health data, cultural practices, or marginalized identities. Another example is how research in NLP lacks the geographical diversity and participatory research can help to mitigate it. The Masakhane project for African NLP involves native speakers in annotation and validation to preserve linguistic and cultural accuracy(Nekoto et al. 2020).

3.3 Model Design

Lived experience plays a critical role in aligning AI system design with the social realities and contextual nuances of users. Participatory design (Muller and Kuhn 1993) and value-sensitive design (VSD) frameworks (Umbrello and De Bellis 2018) demonstrate how user narratives — especially accounts of exclusion, discomfort, or misrecognition — can inform concrete design decisions, such as refining system logic, interface affordances, or feedback mechanisms. These approaches help define abstract technical goals like fairness, interpretability, or accuracy in domain-specific and socially meaningful ways. Human-AI collaboration methods, particularly human-in-the-loop systems (Sicilia, Gates, and Alikhani 2023; Robertson et al. 2024), operationalize this alignment by incorporating ongoing feedback from community members or domain experts to guide data labeling, decision-making, and model refinement. This iterative engagement ensures that models are not only technically accurate but also culturally relevant, emotionally attuned, and ethically grounded. Far from being at odds with lived experience, human-AI collaboration offers a robust strategy for embedding it throughout the AI development pipeline.

3.4 Model Evaluation and Testing

Developers should invite users or stakeholders affected by the AI systems to test and evaluate its outputs in real-world or simulated scenarios (McKenna, Nelson, and Maguire 2024; Beames et al. 2021). Participatory evaluation by users or community-centric testing can surface harms, usability issues, and unintended effects that are invisible to developers. Koenecke et al. (2020) demonstrated how racial disparities in speech recognition systems became evident when testing involved diverse users, showing that systems performed significantly worse on Black speakers. Scenario-based testing (Carrol 1999; Rosson and Carroll 2007), grounded in real-life contexts from stakeholders such as teachers, patients, and gig workers, helps surface edge cases and bias tied to specific identities or environments. Structured workshops with affected communities can further contextualize model errors and unpack their real-world implications.

3.5 Post-deployment Monitoring

A feedback loop is needed to be established if we wanted to implement lived experiments into post deployment monitoring. Feedback loops can continuously surface real world usage insights, harms, and unintended consequences. Rather than relying completely on technical performance metrics, systems should incorporate participatory monitoring mechanisms such as community reporting tools, ethnographic studies, or user diaries that allow diverse stakeholders to share how AI impacts them in daily practice. This is especially vital for AI applications, where language, context, and identity intersect in complex ways. A growing body of research emphasizes continuous post-deployment audits rooted in community experiences. For instance, (Koenecke et al. 2020) in "Racial disparities in automated speech recognition" demonstrate how overlooking user variation can lead to discrimination, highlighting the need for real-world evaluations involving diverse populations.

3.6 Role of Policies in Integration of Human Lived Experiences

Policies can embed lived experience into AI development through a range of mechanisms across the AI life cycle. Policies can mandate participatory design processes to ensure the inclusion of community experiences during the development of AI systems. For example, Costanza-Chock (2020) argues that marginalized community experiences should be actively involved in defining what problems AI systems solve and how they are implemented. Public-sector procurement policies—such as New York City's Automated Decision Systems Task Force have begun to recommend participatory mechanisms for algorithmic accountability. Policies can focus on making technical documentation that integrates real-world and sociocultural contexts. Mitchell et al. (2019) introduced Model Cards, and Gebru et al. (2021) proposed Datasheets for Datasets, both advocating for the inclusion of intended use cases, user feedback, and potential risks. Countries should implement a governmental AI accountability policy, requiring public agencies to disclose how automated systems may affect rights and freedoms. Raji et al. (2020) in "Closing the AI Accountability Gap" propose a structured audit framework that includes community feedback as a key accountability mechanism. These formats create transparency and ensure systems are not deployed in ways that contradict the values and lived experiences of their users.

4 A Closer look at LEAF

To demonstrate the applicability of our framework across diverse domains, we present four case studies. These examples show how integrating lived experiences during the problem definition and development stages of AI leads to more context-aware, ethical, and socially aligned systems. Each case study should exemplifies one or more aspects of the framework (e.g., participatory design, contextual evaluation, post-deployment monitoring).

4.1 Case Study 1 : Students and the Autograder

In this section we use the scenario of AI application within schools.With the growing digitization of educational practices, computers have become integral to educational institutions. Teaching computer science has been a challenge due to the continuously moving goal post. And for the final push recently the advent of large language models has created for a challenging yet opportunistic environment where technology has disrupted somewhat the natural flow of things. Some major challenges for educational AI include misinformation, hallucination, privacy concerns and rising expenses of running such systems (Zainuddin 2024).

The Problem We take the sample case of a study (Li et al. 2023) that illustrated how automatic grading can impact learning in students. The study was conducted in a 600-student, online introductory computer science course for non-majors at the University of Illinois in Fall 2021, focused on teaching Python and Excel. The assignment was a Explain in Plain English (EiPE) problem. EiPE rose in prominence as a method to assess students' ability to read code and discuss its behavior at a high level of abstraction

(Whalley et al. 2006). The course used a custom autograder with 87% accuracy to score EiPE problems, and the study examined how its grading errors affected student learning. This autograder was specifically developed for use in the course. The study evaluated how false positives and false negatives impact students' learned outcome.

What Did the Study Find? They used Bayesian hierarchical generalized linear models to analyze participant behavior on practice and post-test questions, predicting learning outcomes, self-assessment accuracy, and feedback engagement time, while applying *weakly informative priors* to ensure reliable inference despite a small sample size. The study found that when the AI grader provided overall positive feedback, students were less likely to read the detailed feedback and more likely to reject any negative or incorrect evaluations it gave. When the main goal is learning, it's important to avoid false positives—but this study shows we need real data to weigh the trade-offs, since intuitive choices may not lead to the best results. So we see that missing student experiences' in the design led to failures in learning outcomes.

Role of Lived-experience To further understand the points of failure, we revisit the study using LEAF. Formative feedback is a cornerstone of effective learning, and when automated systems misgrade or oversimplify assessment tasks, the educational experience is diminished. This example highlights the need to contextualize problem understanding—recognizing that instructional dynamics are not merely technical, but relational and pedagogical. By centering the perspectives of instructors, tutors, and students, designers can identify how feedback is interpreted, internalized, and acted upon in diverse learning settings.

4.2 Case Study 2 : Conversational Clinical Agents

Early versions of AI have been used for medical diagnosis (McKinney et al. 2020) and virtual healthcare assistance (Fitzpatrick, Darcy, and Vierhile 2017). With the advancements in LLMs, AI has the potential to transform the field of healthcare through increasing diagnosis efficiency (dia 2025; Williams et al. 2024; Kern, Wu, and Chao 2024), newer scientific discoveries (Theodoris et al. 2023; M. Bran et al. 2024), and democratizing access to medical information (Clusmann et al. 2023). However, integrating AI to real-world use-cases in a high-risk domain such as healthcare requires careful considerations related to AI model's performance and broader implications attached to the use of AI in healthcare.

The Problem Prior work have increasingly focused on developing and evaluating diagnostic AI systems for single-turn question answering or knowledge retrieval, often benchmarking AI models against medical exams or clinical QA datasets (Singhal et al. 2023; Jin et al. 2024; Singhal et al. 2025). While such approaches have provided insights about the shortcomings of AI models, these often fail to capture the nuances and complexity of real-world experiences of patients healthcare providers (Blagec et al. 2023; Jacob et al. 2025). Additionally, real-world multi-turn clinical conversations require additional evaluation axes such as empathy, trust-building, relationship-building, respect for the individual and communication efficacy (Jacob et al. 2025; Albahri et al. 2023). These dimensions of evaluations are important for supportive healthcare communication. However, developing holistic evaluation frameworks for AI in healthcare remains an open challenge.

What Did the Study Find? In response to the challenges outlined above, Tu et al. (2025) introduced AMIE (Articulate Medical Intelligence Explorer), a large language model designed for multi-turn diagnostic clinical conversations. They introduced a self-play based simulation environment that took account of the lived-experiences of individuals using vignettes belonging to different demographics background. By capturing the contextual richness of patient encounters, the study foregrounded both clinician and patient perspectives through a dual-metric evaluation framework. This included clinician-centric and patient-centric metrics assessed via automated and human evaluations. Using a combination of automated and human-evaluation, authors observed that AIME outperformed primary care physicians across 28 out of 32 evaluation axes from the specialist physician perspective and 24 out of 26 evaluation axes from the patient actor perspective.

Role of Lived Experience By centering the lived experiences of both patients and clinicians, this work offers a compelling model for integrating experiential knowledge into the design and evaluation of medical AI systems, thereby enhancing their contextual sensitivity and real-world applicability. This dual-perspective design integrates a multi-centered human layer to the validation of medical AI systems, enabling a more holistic and grounded evaluation of AI's real-world readiness. As illustrated within this example, lived experience is of vital importance within healthcare domain. Past works have highlighted that those directly affected by health issues possess unique insights that can significantly improve healthcare systems, research, policies, and programs (Sartor 2023). However, integrating lived experience based insights in AI based systems has been seen as a challenge, where past works have shown the LLMs fail to account for experiences based on race (Yang et al. 2024), gender (Pfohl et al. 2024), languages spoken (Jin et al. 2024), and culture (Omar et al. 2025). Additionally, past works have also shown that LLMs suffer from lack of experiential knowledge that healthcare providers gain through practice (Chandra et al. 2025b).

4.3 Case Study 3 : Gods and Machines

In this section, we examine the importance of cultural alignment in AI systems, focusing on how the integration of cultural values, beliefs, and practices into AI development can impact the effectiveness, integrity and actual use of these systems (Bravansky, Trhlik, and Barez 2025). Cultural alignment refers to the extent to which AI technologies consider and respect the cultural contexts in which they operate (Gabriel 2020). When AI systems are developed without such alignment, they risk reinforcing biases, causing harm, or overlooking critical cultural nuances (Liu 2024). We use the example of AI's engagement with sacred religious texts to highlight the challenges and implications of cultural misalignment in AI technologies, for specific uses.

The Problem In the context of AI, particularly those that process or interpret culturally significant data (such as religious texts), it is important not to treat the data as neutral or context-free, but embedded within complex historical, cultural, and spiritual frameworks.For example, AI models analyzing sacred texts like the Bible or Quran must respect their religious, cultural, and historical significance beyond just linguistic content. Thus the approach needs to account for how these texts are interwoven with cultural identities, belief systems, and traditions, so as to not create a misalignment between the system's design and the communities it serves. A key concern centers on AI's capacity to comprehend and reproduce the deeply personal and experiential dimensions of religious life (Tampubolon and Nadeak 2024). The lack of cultural alignment in AI can result in systems that fail to respect the spiritual significance of these texts or inadvertently perpetuate cultural erasure (Qadri et al. 2025).

What Did the Study Find? Hutchinson's (Hutchinson 2024) study highlights how sacred religious texts are frequently used in AI research (for machine translation, corpus creation, and data analysis) without adequate attention to their cultural or spiritual significance. Texts like the Bible and the Quran are often selected for their size, multilingual content, and accessibility, rather than their religious meaning. This reflects a broader tendency in AI to treat data as purely informational, neglecting the embedded cultural and ethical dimensions (Tampubolon and Nadeak 2024). Building on this, scholars such as Bostrom (Robert 2017) and Floridi (Cath et al. 2018) have raised ethical concerns about AI's role in religious contexts, questioning the authenticity of AI-mediated religious experiences and the appropriateness of delegating spiritual authority to non-sentient systems (Tampubolon and Nadeak 2024).

Role of Lived Experiences To prevent the risks of cultural misalignment, Hutchinson (Hutchinson 2024) advocated for a more nuanced and culturally sensitive approach to AI development. As highlighted in our framework, AI systems engaging with sacred or culturally significant data must be designed with an awareness that such texts are not neutral but are socio-technical and thus embedded with cultural, religious, and historical meanings that shape the communities they represent. Religious and cultural heritages have long histories of sharing and generating knowledge through folk tales, rituals, and other communal practices (Çağın Zort et al. 2023). For example, much of these traditions often depend not only on written texts but also on oral storytelling and embodied experiences to pass knowledge from one generation to the next. Lived experience thus plays a crucial role in shaping how stories and meanings are created, adapted, and maintained, as telling the story itself becomes a way of constructing meaning. As proposed by scholars of religion, artificial intelligence and machine learning, AI can serve as a tool to advance the study of religion (Yao 2024), while also enabling religious frameworks to inform our understanding of AI itself (Reed 2021).

4.4 Case Study 4 : AI for Task Instruction

Multi-modal systems integrate various input and output modalities (such as speech, touch, gesture, gaze, and haptics) to enable richer and natural interaction between humans and machines. While traditionally measured through technical performance and usability metrics, the real-world impact of these systems often hinges on the lived experiences of users. The recent advent of LLMs has also combined vision and language tasks through the use of Vision-Language Models (VLMs) (Nguyen et al. 2025). From setting the temperature of your fridge to building one yourself, the internet comes with instructional videos. However, these videos are hard to follow, for example, the system shown uses a different version of the model than the one currently in use. In such cases, it is easier to ask the AI system specific questions related to your model of the system or device. Using applications with multiple modalities, it will be helpful for the end user to have an image input augmented with the natural language input when asking questions specific to a task.

The Problem Mohan's (Mohan et al. 2019) research is in the direction of apprenticeship learning, where the user can be taught to perform seemingly complicated tasks like changing the cartridge on a printer with near real-time instructions using computer vision-guided instructions. Wang et al. (Wang et al. 2019) demonstrate similar solutions from a robotics perspective with a UR5 arm mounted on a scooter that reaches out for objects and places them in a bag when pointed to by the user, easily extendable to haptic feedback and speech instructions. Nguyen et al. (Nguyen et al. 2025) present a system for video question-answering that lets users search for specific questions ranging from technical to everyday instructional tasks, and responds with instructional video snippets for each step needed to perform a task.

What Did the Study Find? While these studies provide us with solutions to good instruction generation using VLMs, the proposed solutions faces the challenge of noise in language, speech and vision, in case the input is distorted with noise (Malik, Crowder, and Mingolla 2023a,b). The point of failure is lack of accounting for the mental models of task performance may differ user to user (Allen 1997). A visual overload of information and decision-making demands can hinder overall understanding of the task (Sephton 2013). The solutions also pose privacy and security concerns in case of processing private and sensitive data in an open setting, say reading out banking information in a public space.

Role of Lived Experiences As mentioned in the framework, understanding user mental models for learning tasks, the system could perform a context-aware (CA) modality switching to pre-process the input before sending it to the model, helping cut down the noise in the system. CA also enables these systems to consider their operational environment and location, helping to ensure compliance with relevant privacy standards (Schaub, Könings, and Weber 2015).

This dual benefit of cognitive alignment and contextual sensitivity enhances both system usability and trustworthiness.

5 Discussion

Understanding and integrating human lived experiences in AI models is crucial for ensuring AI systems align with human values, needs, and well-being. Lived experiences shape how individuals interact with LLMs, influencing AI safety, design, and knowledge representation. Existing research highlights risks such as over-reliance (Passi and Vorvoreanu 2022), compromised trust (Buçinca, Malaya, and Gajos 2021), and psychological harm (Pałka 2023; Chandra et al. 2025a), which are mediated by individual contexts (Küper and Krämer 2025). These can be mitigated in part by inclusion of lived experiences. For instance, we find that personal experiences (and reflections) can play a pivotal role in defining the consumption of technology. For humans, cognition involves a complex interplay between external perceptions and internal explorations (Barsalou 2014; Mead 1934; Antony 2001). This work contributes to advancing that understanding by offering a clearer, more systematic approach—through a practical framework—for integrating lived experiences into AI development to foster better inclusivity. In this section, we discuss the broader implication of our work regarding importance of inclusion of pluralistic experiences, incorporating lived experiences with changing society and highlight the dynamic nature of the LEAF. Finally, we discuss the limitations of our work.

5.1 Importance of Inclusion of Pluralistic Experiences

In recent years, interactions with technology have increasingly shaped how individuals perceive their sense of self and community. For instance, echo chambers formed by personalized algorithms as well as engagements with AI conversational agents can create the illusion of singular, enclosed realities (Belk 2013; Feige and Choubak 2019). The concept of lived experience, by contrast, is rooted in interpretiveness (Ellis 1992). This interpretive nature enables multiple, coexisting perceptions of the same event or interaction. Within this plurality lies the unique richness of human perspective and creativity. By embedding such diversity into the design of AI tools, we not only center human involvement in technological systems but also enhance their effectiveness.

5.2 Incorporating Lived Experiences in an Ever-Evolving World

Human experiences and expectations are not static, they are constantly changing in response to changes in society around us, and technological advancements (Russon 2003; Dunfey 2023; Harvard Business Review 2003). At the same time, with the rapid development of AI and its increasing integration into human ecosystems, the way individuals interact with technology and perceive it is undergoing transformation (Raees et al. 2024; Afroogh et al. 2024). As a result, the notion of human lived experience in the age of AI is itself evolving. While our work presents dimensions of lived experience based on past research across various disciplines, it is likely that new AI-specific dimensions of human lived experiences may emerge in the future, something future work could explore. Moreover, as human-AI interactions become more frequent and complex with time, additional stages may be required and introduced in AI design and development pipeline to accommodate these new experiential factors.

5.3 Dynamism Within the LEAF

Beyond establishing the relevance and dimensions of lived experience, it is equally important to articulate a path forward. While comprehensive, our framework remains flexible, allowing new stages to be added or existing ones to be modified based on specific use cases or technological advancements. Similarly, other studies have emphasized that the integration of researchers' evolving positionalities and lived experiences can critically influence not only the framing of research questions but also the interpretive lenses applied during system design and evaluation (Dembele et al. 2024; De, Kanthawala, and Maddox 2025). This means inherent systems often suffer with lack of dynamism when those provisions are not provided.

5.4 Limitations and Future Work

Finally, while this framework has been contextualized within domains such as healthcare, religion, education, and everyday life, its broader applicability remains to be discussed and validated. Future work should explore its relevance in additional sectors, such as finance, entertainment, legal systems, and more where lived experience may manifest differently. Advancing this work will also require the development of new tools and metrics capable of capturing the nuanced, multifaceted nature of lived experience. We envision future research extending this framework through domain-specific adaptations, innovative methodological approaches, and large-scale empirical validation.

6 Conclusion

This paper has underscored the critical role of lived experiences in shaping human-centered, contextually grounded, and ethically aligned AI systems. Through theoretical grounding and illustrative scenarios, we have shown that the exclusion of lived, subjective experiences from the AI design pipeline can lead to systems that misalign with users' intentions, contexts, and values—resulting in miscommunication, harm, and systemic bias. Our discussion bridges gaps between technical design, social experience, and cultural specificity, advocating for methodological pluralism that includes first-person perspectives, embodied interactions, and contextual knowledge. We argue that integrating lived experiences is not merely an ethical imperative but also a design necessity—essential for closing the gulf between user intentions and system behavior, and for fostering trust, usability, and inclusivity. As AI systems increasingly mediate everyday decision-making and identity formation, this work calls for a sustained commitment to embedding the pluralities of human life into the design and development of intelligent technologies.

References

2025. Medical large language model for diagnostic reasoning across specialties. *Nature Medicine*, 31(3): 743–744.

Adeofe, L. 1995. Artificial intelligence and subjective experience. In *Proceedings of Southcon '95*, 403–408.

Afroogh, S.; Akbari, A.; Malone, E.; Kargar, M.; and Alambeigi, H. 2024. Trust in AI: progress, challenges, and future directions. *Humanities and Social Sciences Communications*, 11(1): 1–30.

Ajjawi, R.; Bearman, M.; Luong, V.; O'Brien, B. C.; and Varpio, L. 2024. Researching lived experience in health professional education. *Medical Education*, 58(9): 1049–1057.

Albahri, A. S.; Duhaim, A. M.; Fadhel, M. A.; Alnoor, A.; Baqer, N. S.; Alzubaidi, L.; Albahri, O. S.; Alamoodi, A. H.; Bai, J.; Salhi, A.; et al. 2023. A systematic review of trustworthy and explainable artificial intelligence in healthcare: Assessment of quality, bias risk, and data fusion. *Information Fusion*, 96: 156–191.

Allen, R. B. 1997. Mental models and user models. In *Handbook of human-computer interaction*, 49–63. Elsevier.

Allison, P.; and Pomeroy, E. 2000. How shall we "know?" Epistemological concerns in research in experiential education. *Journal of Experiential Education*, 23(2): 91–98.

Amershi, B. 2020. Culture, the process of knowledge, perception of the world and emergence of AI. *AI & SOCIETY*, 35(2): 417–430.

An, H.; Acquaye, C.; Wang, C.; Li, Z.; and Rudinger, R. 2024. Do Large Language Models Discriminate in Hiring Decisions on the Basis of Race, Ethnicity, and Gender? *arXiv preprint arXiv:2406.10486*.

Antony, M. V. 2001. Is 'consciousness' ambiguous? *Journal of Consciousness Studies*, 8(2): 19–44.

Armutat, S.; Wattenberg, M.; and Mauritz, N. 2024. Artificial Intelligence: Gender-Specific Differences in Perception, Understanding, and Training Interest. In *International Conference on Gender Research*, 36–43. Academic Conferences International Limited.

Barsalou, L. W. 2014. *Cognitive psychology: An overview for cognitive scientists*. Psychology Press.

Beames, J. R.; Kikas, K.; O'Gradey-Lee, M.; Gale, N.; Werner-Seidler, A.; Boydell, K. M.; and Hudson, J. L. 2021. A new normal: integrating lived experience into scientific data syntheses. *Frontiers in psychiatry*, 12: 763005.

Belk, R. W. 2013. Extended self in a digital world. *Journal of consumer research*, 40(3): 477–500.

Bingley, W. J.; Curtis, C.; Lockey, S.; Bialkowski, A.; Gillespie, N.; Haslam, S. A.; Ko, R. K.; Steffens, N.; Wiles, J.; and Worthy, P. 2023. Where is the human in human-centered AI? Insights from developer priorities and user experiences. *Computers in Human Behavior*, 141: 107617.

Birhane, A.; Ruane, E.; Laurent, T.; S. Brown, M.; Flowers, J.; Ventresque, A.; and L. Dancy, C. 2022. The Forgotten Margins of AI Ethics. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*, FAccT '22, 948–958. New York, NY, USA: Association for Computing Machinery. ISBN 9781450393522.

Blagec, K.; Kraiger, J.; Frühwirt, W.; and Samwald, M. 2023. Benchmark datasets driving artificial intelligence development fail to capture the needs of medical professionals. *Journal of Biomedical Informatics*, 137: 104274.

Boud, D.; Keogh, R.; and Walker, D. 2013. *Reflection: Turning experience into learning*. Routledge.

Bravansky, M.; Trhlik, F.; and Barez, F. 2025. Rethinking ai cultural evaluation. *arXiv preprint arXiv:2501.07751*.

Brett, J.; Staniszewska, S.; Mockford, C.; Herron-Marx, S.; Hughes, J.; Tysall, C.; and Suleman, R. 2014. Mapping the impact of patient and public involvement on health and social care research: a systematic review. *Health expectations*, 17(5): 637–650.

Brogden, J.; de Haan, Z.; Gorban, C.; Hockey, S. J.; Hutcheon, A.; Iorfino, F.; Song, Y. J. C.; Scott, E.; Hickie, I. B.; and McKenna, S. 2024. Enhancing Research Involvement of Young People With Lived Expertise: Reflecting on Experiences in Digital Mental Health Research. *Journal of Medical Internet Research*, 26: e55441.

Buçinca, Z.; Malaya, M. B.; and Gajos, K. Z. 2021. To trust or to think: cognitive forcing functions can reduce overreliance on AI in AI-assisted decision-making. *Proceedings of the ACM on Human-computer Interaction*, 5(CSCW1): 1–21.

Bunnin, N.; and Yu, J. 2008. *The Blackwell dictionary of Western philosophy*. John Wiley & Sons.

Cantley, L. 2025. Indigenous data sovereignty: What can yarning teach us? *Australian Social Work*, 78(2): 133–144.

Capel, T.; and Brereton, M. 2023. What is human-centered about human-centered AI? A map of the research landscape. In *Proceedings of the 2023 CHI conference on human factors in computing systems*, 1–23.

Carrol, J. M. 1999. Five reasons for scenario-based design. In *Proceedings of the 32nd annual hawaii international conference on systems sciences. 1999. hicss-32. abstracts and cd-rom of full papers*, 11–pp. IEEE.

Casey, P. J. 2023. Lived Experience: Defined and Critiqued. *Critical Horizons*, 24(3): 282–297.

Cath, C.; Wachter, S.; Mittelstadt, B.; Taddeo, M.; and Floridi, L. 2018. Artificial intelligence and the 'good society': the US, EU, and UK approach. *Science and engineering ethics*, 24: 505–528.

Chandra, M.; Naik, S.; Ford, D.; Okoli, E.; De Choudhury, M.; Ershadi, M.; Ramos, G.; Hernandez, J.; Bhattacharjee, A.; Warreth, S.; and Suh, J. 2025a. From Lived Experience to Insight: Unpacking the Psychological Risks of Using AI Conversational Agents. In *Proceedings of the 2025 ACM Conference on Fairness, Accountability, and Transparency*, FAccT '25, 975–1004. New York, NY, USA: Association for Computing Machinery. ISBN 9798400714825.

Chandra, M.; Sriraman, S.; Verma, G.; Khanuja, H. S.; Campayo, J. S.; Li, Z.; Birnbaum, M. L.; and De Choudhury, M. 2025b. Lived Experience Not Found: LLMs Struggle to Align with Experts on Addressing Adverse Drug Reactions from Psychiatric Medication Use. In Chiruzzo, L.; Ritter, A.; and Wang, L., eds., *Proceedings of the 2025 Conference* *of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, 11083–11113. Albuquerque, New Mexico: Association for Computational Linguistics. ISBN 979-8-89176-189-6.

Chiorri, C.; and Vannucci, M. 2024. The subjective experience of autobiographical remembering: Conceptual and methodological advances and challenges. *Journal of Intelligence*, 12(2): 21.

Clusmann, J.; Kolbinger, F. R.; Muti, H. S.; Carrero, Z. I.; Eckardt, J.-N.; Laleh, N. G.; Löffler, C. M. L.; Schwarzkopf, S.-C.; Unger, M.; Veldhuizen, G. P.; et al. 2023. The future landscape of large language models in medicine. *Communications medicine*, 3(1): 141.

Coolen, M. 2014. Bodily experience and experiencing one's body. *Plessner's Philosophical Anthropology*, 111.

Cosley, D.; Churchill, E.; Forlizzi, J.; and Munson, S. A. 2017. Introduction to This Special Issue on the Lived Experience of Personal Informatics. *Human–Computer Interaction*, 32(5–6): 197–207.

Costanza-Chock, S. 2020. *Design justice: Community-led practices to build the worlds we need*. The MIT Press.

De, A.; Kanthawala, S.; and Maddox, J. 2025. Who Gets Heard? Calling Out the "Hard-to-Reach" Myth for Non-WEIRD Populations' Recruitment and Involvement in Research. In *Proceedings of the 2025 ACM Conference on Fairness, Accountability, and Transparency*, FAccT '25, 855–867. New York, NY, USA: Association for Computing Machinery. ISBN 9798400714825.

Dembele, L.; Nathan, S.; Carter, A.; Costello, J.; Hodgins, M.; Singh, R.; Martin, B.; and Cullen, P. 2024. Researching with lived experience: a shared critical reflection between co-researchers. *International Journal of Qualitative Methods*, 23: 16094069241257945.

Dictionary, O. 2025. https://www.oxfordreference.com/display/10.1093/oi/authority.20110803100109997. [Accessed 18-05-2025].

Dieumegard, G.; Nogry, S.; Ollagnier-Beldame, M.; and Perrin, N. 2021. Lived experience as a unit of analysis for the study of learning. *Learning, Culture and Social Interaction*, 31: 100345.

Do, H. J.; Brachman, M.; Dugan, C.; Pan, Q.; Rai, P.; Johnson, J. M.; and Thawani, R. 2024. Evaluating What Others Say: The Effect of Accuracy Assessment in Shaping Mental Models of AI Systems. *Proceedings of the ACM on Human-Computer Interaction*, 8(CSCW2): 1–26.

Dunfey, T. S. 2023. What is Social Change and Why Should We Care? https://www.snhu.edu/about-us/newsroom/social-sciences/what-is-social-change. [Accessed 22-05-2025].

Ellis, C. 1992. *Investigating subjectivity: Research on lived experience*, volume 139. Sage.

Fan, Y.; Tang, L.; Le, H.; Shen, K.; Tan, S.; Zhao, Y.; Shen, Y.; Li, X.; and Gašević, D. 2025. Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance. *British Journal of Educational Technology*, 56(2): 489–530.

Farrell, E. 2020. Researching lived experience in education: Misunderstood or missed opportunity? *International Journal of Qualitative Methods*, 19: 1609406920942066.

Feige, S.; and Choubak, M. 2019. Compensating People with lived experience: best Practices from the literature. *Guelph, ON: Community Engaged Scholarship Institute*.

Feldhay Brenner, R. 1994. Edith Stein: A reading of her feminist thought. *Studies in Religion/Sciences religieuses*, 23(1): 43–56.

Fitzpatrick, K. K.; Darcy, A.; and Vierhile, M. 2017. Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (Woebot): a randomized controlled trial. *JMIR mental health*, 4(2): e7785.

Forum, W. E. 2024. AI Value Alignment: Guiding Artificial Intelligence Towards Shared Human Goals. https://www.weforum.org/publications/ai-value-alignment-guiding-artificial-intelligence-towards-shared-human-goals/. [Accessed 18-05-2025].

Frank, A.; Gleiser, M.; and Thompson, E. 2024. *The blind spot: Why science cannot ignore human experience*. MIT Press.

Freiman, O. 2023. Making sense of the conceptual nonsense 'trustworthy AI'. *AI Ethics*, 3: 1351–1360.

Frempong, G.; and Kadam, R. 2024. Harmonizing AI and Human Values: The Ubuntu Approach to Super Alignment in OpenAI's Initiatives. In *International Conference on Human-Computer Interaction*, 186–193. Springer.

Gabriel, I. 2020. Artificial intelligence, values, and alignment. *Minds and machines*, 30(3): 411–437.

Garko, M. G. 1999. Existential phenomenology and feminist research: The exploration and exposition of women's lived experiences. *Psychology of Women Quarterly*, 23(1): 167–175.

Gebru, T.; Morgenstern, J.; Vecchione, B.; Vaughan, J. W.; Wallach, H.; Iii, H. D.; and Crawford, K. 2021. Datasheets for datasets. *Communications of the ACM*, 64(12): 86–92.

Giles, D.; Smythe, E.; and Spence, D. 2012. Exploring relationships in education: A phenomenological inquiry. *Australian Journal of Adult Learning*, 52(2): 214–236.

Ginn, R. A. 2016. *Promoting Cultural Awareness in Preservice Teachers: Findings from Lived Experiences during a Cultural Historical Immersion Experience*. Northcentral University.

Girju, R. 2023. Understanding lived experience: Bridging artificial intelligence and natural language processing with humanities and social sciences. In *IOP Conference Series: Materials Science and Engineering*, volume 1292, 012020. IOP Publishing.

Goodare, H.; and Lockwood, S. 1999. Involving patients in clinical research: improves the quality of research.

Haim-Litevsky, D.; Komemi, R.; and Lipskaya-Velikovsky, L. 2023. Sense of belonging, meaningful daily life participation, and well-being: Integrated investigation. *International journal of environmental research and public health*, 20(5): 4121.

Han, S.; Kelly, E.; Nikou, S.; and Svee, E.-O. 2022. Aligning artificial intelligence with human values: reflections from a phenomenological perspective. *AI & SOCIETY*, 1–13.

Happell, B.; and Roper, C. 2007. Consumer participation in mental health research: articulating a model to guide practice. *Australasian Psychiatry*, 15(3): 237–241.

Harvard Business Review. 2003. Technology and Human Vulnerability — hbr.org. https://hbr.org/2003/09/technology-and-human-vulnerability. [Accessed 22-05-2025].

Heidegger, M.; Macquarrie, J.; Robinson, E.; et al. 1962. Being and time.

Howard, M. W. 2018. Memory as perception of the past: compressed time inMind and brain. *Trends in cognitive sciences*, 22(2): 124–136.

Hutchinson, B. 2024. Modeling the Sacred: Considerations when Using Religious Texts in Natural Language Processing. *arXiv preprint arXiv:2404.14740*. Submitted on 23 Apr 2024, last revised 25 Jun 2024.

Jacob, C.; Brasier, N.; Laurenzi, E.; Heuss, S.; Mougiakakou, S.-G.; Cöltekin, A.; and Peter, M. K. 2025. AI for IMPACTS Framework for Evaluating the Long-Term Real-World Impacts of AI-Powered Clinician Tools: Systematic Review and Narrative Synthesis. *Journal of Medical Internet Research*, 27: e67485.

Jin, Y.; Chandra, M.; Verma, G.; Hu, Y.; De Choudhury, M.; and Kumar, S. 2024. Better to ask in english: Cross-lingual evaluation of large language models for healthcare queries. In *Proceedings of the ACM Web Conference 2024*, 2627–2638.

Jonassen, D. H.; and Henning, P. 1999. Mental models: Knowledge in the head and knowledge in the world. *Educational technology*, 37–42.

Kahneman, D.; and Riis, J. 2005. Living, and thinking about it: Two perspectives on life. *The science of well-being*, 1(285-304): 3.

Kern, F. B.; Wu, C.-T.; and Chao, Z. C. 2024. Assessing novelty, feasibility and value of creative ideas with an unsupervised approach using GPT-4. *British Journal of Psychology*.

Koenecke, A.; Nam, A.; Lake, E.; Nudell, J.; Quartey, M.; Mengesha, Z.; Toups, C.; Rickford, J. R.; Jurafsky, D.; and Goel, S. 2020. Racial disparities in automated speech recognition. *Proceedings of the national academy of sciences*, 117(14): 7684–7689.

Korteling, J. H.; van de Boer-Visschedijk, G. C.; Blankendaal, R. A.; Boonekamp, R. C.; and Eikelboom, A. R. 2021. Human-versus artificial intelligence. *Frontiers in artificial intelligence*, 4: 622364.

Kruks, S. 1992. Gender and subjectivity: Simone de Beauvoir and contemporary feminism. *Signs: Journal of Women in Culture and Society*, 18(1): 89–110.

Kruks, S. 2014. Women's 'lived experience': feminism and phenomenology from Simone de Beauvoir to the present. *The SAGE handbook of feminist theory*, 75–92.

Küper, A.; and Krämer, N. 2025. Psychological traits and appropriate reliance: Factors shaping trust in AI. *International Journal of Human–Computer Interaction*, 41(7): 4115–4131.

Lee, H. S.; Wright, C.; Ferranto, J.; Buttimer, J.; Palmer, C. E.; Welchman, A.; Mazor, K. M.; Fisher, K. A.; Smelson, D.; O'Connor, L.; et al. 2025. Artificial intelligence conversational agents in mental health: Patients see potential, but prefer humans in the loop. *Frontiers in Psychiatry*, 15: 1505024.

Li, T. W.; Hsu, S.; Fowler, M.; Zhang, Z.; Zilles, C.; and Karahalios, K. 2023. Am I wrong, or is the autograder wrong? Effects of AI grading mistakes on learning. In *Proceedings of the 2023 ACM Conference on International Computing Education Research-Volume 1*, 159–176.

Liu, Z. 2024. Cultural Bias in Large Language Models: A Comprehensive Analysis and Mitigation Strategies. *Journal of Transcultural Communication*, (0).

Luckin, R.; and Holmes, W. 2016. Intelligence unleashed: An argument for AI in education.

M. Bran, A.; Cox, S.; Schilter, O.; Baldassari, C.; White, A. D.; and Schwaller, P. 2024. Augmenting large language models with chemistry tools. *Nature Machine Intelligence*, 6(5): 525–535.

Mackee, A. J. 2024. Lived Experiences — Definition — docmckee.com. https://docmckee.com/cj/docs-research-glossary/lived-experiences-definition/. [Accessed 27-04-2025].

Maggs-Rapport, F. 2001. 'Best research practice': in pursuit of methodological rigour. *Journal of Advanced Nursing*, 35(3): 373–383.

Magrini, J. 2011. Recovering a Phenomenological-Hermeneutic Understanding of the Human Being as" Learner": Exploring the Authentic Teacher-Pupil Relationship.

Malik, G.; Crowder, D.; and Mingolla, E. 2023a. Extreme image transformations affect humans and machines differently. *Biological Cybernetics*, 117(4): 331–343.

Malik, G.; Crowder, D.; and Mingolla, E. 2023b. Extreme Image Transformations Facilitate Robust Latent Object Representations. *arXiv preprint arXiv:2310.07725*.

Markham, A. N.; and Pereira, G. 2019. Experimenting with algorithms and memory-making: Lived experience and future-oriented ethics in critical data science. *Frontiers in big Data*, 2: 35.

Markus, H. R.; and Lin, L. R. 1999. Conflictways: Cultural diversity in the meanings and practices of conflict. *Cultural divides: Understanding and overcoming group conflict*, 302–333.

Mascitelli, R. 2000. From experience: harnessing tacit knowledge to achieve breakthrough innovation. *Journal of Product Innovation Management: an International Publication of the Product Development & Management Association*, 17(3): 179–193.

Matu, J. B.; and Perez-Johnston, A. 2024. The importance of incorporating lived experience and identity in promoting cultural diversity and sustainability in community college and education: a case study of Community College of Allegheny County. *International Journal of Sustainability in Higher Education*, 25(3): 470–488.

May, C.; Wang, A.; Bordia, S.; Bowman, S. R.; and Rudinger, R. 2019. On measuring social biases in sentence encoders. *arXiv preprint arXiv:1903.10561*.

McIntosh, I.; and Wright, S. 2019. Exploring what the notion of 'lived experience'offers for social policy analysis. *Journal of social policy*, 48(3): 449–467.

McKenna, S.; Nelson, E.; and Maguire, A. 2024. Bringing data to life: A model for involving lived experience in data-driven research. *International Journal of Population Data Science*, 9(5).

McKinney, S. M.; Sieniek, M.; Godbole, V.; Godwin, J.; Antropova, N.; Ashrafian, H.; Back, T.; Chesus, M.; Corrado, G. S.; Darzi, A.; et al. 2020. International evaluation of an AI system for breast cancer screening. *Nature*, 577(7788): 89–94.

Mead, G. H. 1934. Mind, self, and society from the standpoint of a social behaviorist.

Miles, M.; Chapman, Y.; Francis, K.; and Taylor, B. 2013. Exploring Heideggerian hermeneutic phenomenology: A perfect fit for midwifery research. *Women and Birth*, 26(4): 273–276.

Mitchell, M.; Wu, S.; Zaldivar, A.; Barnes, P.; Vasserman, L.; Hutchinson, B.; Spitzer, E.; Raji, I. D.; and Gebru, T. 2019. Model cards for model reporting. In *Proceedings of the conference on fairness, accountability, and transparency*, 220–229.

Mohan, S.; Ramea, K.; Price, B.; Shreve, M.; Eldardiry, H.; and Nelson, L. 2019. Building Jarvis-A Learner-Aware Conversational Trainer. In *IUI Workshops*.

Muchamore, I.; Karanikolas, P.; and Gooding, P. M. 2024. How Lived Experience Expertise Shapes Research and Development in Digital Mental Health. SSRN Electronic Journal. Posted on SSRN, Paper No. 4566018.

Mugari, I.; and Obioha, E. E. 2021. Predictive policing and crime control in the United States of America and Europe: Trends in a decade of research and the future of predictive policing. *Social sciences*, 10(6): 234.

Mugleston, J.; Truong, V. H.; Kuang, C.; Sibiya, L.; and Myung, J. 2025. Epistemology in the Age of Large Language Models. *Knowledge*, 5(1): 3.

Muller, M. J.; and Kuhn, S. 1993. Participatory design. *Communications of the ACM*, 36(6): 24–28.

Naous, T.; Ryan, M. J.; Ritter, A.; and Xu, W. 2023. Having beer after prayer? measuring cultural bias in large language models. *arXiv preprint arXiv:2305.14456*.

Nekoto, W.; Marivate, V.; Matsila, T.; Fasubaa, T.; Kolawole, T.; Fagbohungbe, T.; Akinola, S. O.; Muhammad, S. H.; Kabongo, S.; Osei, S.; et al. 2020. Participatory research for low-resourced machine translation: A case study in african languages. *arXiv preprint arXiv:2010.02353*.

Nguyen, P.; Sengupta, S.; Malik, G.; Gupta, A.; and Min, B. 2025. InsTALL: Context-aware Instructional Task Assistance with Multi-modal Large Language Models. *arXiv preprint arXiv:2501.12231*.

Norhashim, H.; and Hahn, J. 2024. Measuring Human-AI Value Alignment in Large Language Models. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*, volume 7, 1063–1073.

Norman, D. A. 1988. *The psychology of everyday things.* Basic books.

Obermeyer, Z.; Powers, B.; Vogeli, C.; and Mullainathan, S. 2019. Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, 366(6464): 447–453.

Olawade, D. B.; Wada, O. Z.; Odetayo, A.; David-Olawade, A. C.; Asaolu, F.; and Eberhardt, J. 2024. Enhancing mental health with Artificial Intelligence: Current trends and future prospects. *Journal of medicine, surgery, and public health*, 100099.

Olivier, B. 2017. Artificial Intelligence (AI) and being human: What is the difference? *Acta Academica: Critical views on society, culture and politics*, 49(1): 2–21.

Omar, M.; Sorin, V.; Agbareia, R.; Apakama, D. U.; Soroush, A.; Sakhuja, A.; Freeman, R.; Horowitz, C. R.; Richardson, L. D.; Nadkarni, G. N.; et al. 2025. Evaluating and addressing demographic disparities in medical large language models: a systematic review. *International Journal for Equity in Health*, 24(1): 57.

Otado, J.; Kwagyan, J.; Edwards, D.; Ukaegbu, A.; Rockcliffe, F.; and Osafo, N. 2015. Culturally competent strategies for recruitment and retention of African American populations into clinical trials. *Clinical and translational science*, 8(5): 460–466.

O'Connor, S.; and Liu, H. 2024. Gender bias perpetuation and mitigation in AI technologies: challenges and opportunities. *AI & SOCIETY*, 39(4): 2045–2057.

Pałka, P. 2023. AI, Consumers & Psychological Harm. *AI and Consumers,'Larry DiMatteo, Cristina Poncibò, Martin Hogg, Geraint Howells (Eds.), Cambridge University Press (2023/2024)*.

Passi, S.; and Vorvoreanu, M. 2022. Overreliance on AI literature review. *Microsoft Research*, 339: 340.

Patterson, A.; Kinloch, V.; Burkhard, T.; Randall, R.; and Howard, A. 2016. Black feminist thought as methodology: Examining intergenerational lived experiences of Black women. *Departures in Critical Qualitative Research*, 5(3): 55–76.

Pfohl, S. R.; Cole-Lewis, H.; Sayres, R.; Neal, D.; Asiedu, M.; Dieng, A.; Tomasev, N.; Rashid, Q. M.; Azizi, S.; Rostamzadeh, N.; et al. 2024. A toolbox for surfacing health equity harms and biases in large language models. *Nature Medicine*, 30(12): 3590–3600.

Portway, S. M.; and Johnson, B. 2005. Do you know I have Asperger's syndrome? Risks of a non-obvious disability. *Health, Risk & Society*, 7(1): 73–83.

Pufall-Jones, E.; and Mistry, J. 2010. Navigating across Cultures: Narrative Constructions of Lived Experience. *Journal of Ethnographic & Qualitative Research*, 4(3).

Qadri, R.; Davani, A. M.; Robinson, K.; and Prabhakaran, V. 2025. Risks of Cultural Erasure in Large Language Models. *arXiv preprint arXiv:2501.01056*.

Raees, M.; Meijerink, I.; Lykourentzou, I.; Khan, V.-J.; and Papangelis, K. 2024. From explainable to interactive AI: A literature review on current trends in human-AI interaction. *International Journal of Human-Computer Studies*, 103301.

Raji, I. D.; Smart, A.; White, R. N.; Mitchell, M.; Gebru, T.; Hutchinson, B.; Smith-Loud, J.; Theron, D.; and Barnes, P. 2020. Closing the AI accountability gap: Defining an end-to-end framework for internal algorithmic auditing. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*, 33–44.

Reed, R. 2021. AI in Religion, AI for Religion, AI and Religion: Towards a theory of religious studies and artificial intelligence. *Religions*, 12(6): 401.

Rix-Lièvre, G.; Cahour, B.; and Guibourdenche, J. 2024. Understanding Human Activity on the Basis of "Lived Experience". What are the benefits brought by the articulation with other approaches? *Revue d'anthropologie des connaissances*, 18(18-1).

Robert, C. 2017. Superintelligence: Paths, dangers, strategies.

Robertson, J.; Schmidt, T.; Hutter, F.; and Awad, N. 2024. A Human-in-the-Loop Fairness-Aware Model Selection Framework for Complex Fairness Objective Landscapes. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*, volume 7, 1231–1242.

Rooksby, J.; Rost, M.; Morrison, A.; and Chalmers, M. 2014. Personal tracking as lived informatics. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '14, 1163–1172. New York, NY, USA: Association for Computing Machinery. ISBN 9781450324731.

Rosson, M. B.; and Carroll, J. M. 2007. Scenario-based design. In *The human-computer interaction handbook*, 1067–1086. CRC Press.

Russon, J. 2003. *Human experience: Philosophy, neurosis, and the elements of everyday life*. SUNY Press.

Sartor, C. 2023. Mental health and lived experience: The value of lived experience expertise in global mental health. *Cambridge Prisms: Global Mental Health*, 10: e38.

Schaub, F.; Könings, B.; and Weber, M. 2015. Context-adaptive privacy: Leveraging context awareness to support privacy decision making. *IEEE Pervasive Computing*, 14(1): 34–43.

Scheuerman, M. K.; Branham, S. M.; and Hamidi, F. 2018. Safe Spaces and Safe Places: Unpacking Technology-Mediated Experiences of Safety and Harm with Transgender People. *Proc. ACM Hum.-Comput. Interact.*, 2(CSCW).

Schön, D. A. 1979. The reflective practitioner. *New York*.

Schraw, G.; and Dennison, R. S. 1994. Assessing metacognitive awareness. *Contemporary educational psychology*, 19(4): 460–475.

Schwarz, N.; and Clore, G. L. 1996. Feelings and phenomenal experiences. *Social psychology: Handbook of basic principles*, 2: 385–407.

Scott, J. W. 1991. The evidence of experience. *Critical inquiry*, 17(4): 773–797.

Selwyn, N. 2019. *Should robots replace teachers?: AI and the future of education*. John Wiley & Sons.

Sephton, K. A. 2013. *Decision-making under information overload: Visual representation and 'fast and frugal'heuristics as strategies for dealing with information overload*. Ph.D. thesis, Stellenbosch: Stellenbosch University.

Shelby, R.; Rismani, S.; Henne, K.; Moon, A.; Rostamzadeh, N.; Nicholas, P.; Yilla-Akbari, N.; Gallegos, J.; Smart, A.; Garcia, E.; et al. 2023. Sociotechnical harms of algorithmic systems: Scoping a taxonomy for harm reduction. In *Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society*, 723–741.

Shen, H.; Knearem, T.; Ghosh, R.; Alkiek, K.; Krishna, K.; Liu, Y.; Ma, Z.; Petridis, S.; Peng, Y.-H.; Qiwei, L.; et al. 2024a. Towards bidirectional human-ai alignment: A systematic review for clarifications, framework, and future directions. *arXiv preprint arXiv:2406.09264*.

Shen, H.; Knearem, T.; Ghosh, R.; Yang, Y.-J.; Mitra, T.; and Huang, Y. 2024b. Valuecompass: A framework of fundamental values for human-ai alignment. *arXiv preprint arXiv:2409.09586*.

Sicilia, A.; Gates, J. C.; and Alikhani, M. 2023. HumBEL: a human-in-the-loop approach for evaluating demographic factors of language models in human-machine conversations. *arXiv preprint arXiv:2305.14195*.

Siddals, S.; Torous, J.; and Coxon, A. 2024. "It happened to be the perfect thing": experiences of generative AI chatbots for mental health. *npj Mental Health Research*, 3(1): 48.

Singhal, K.; Azizi, S.; Tu, T.; Mahdavi, S. S.; Wei, J.; Chung, H. W.; Scales, N.; Tanwani, A.; Cole-Lewis, H.; Pfohl, S.; et al. 2023. Large language models encode clinical knowledge. *Nature*, 620(7972): 172–180.

Singhal, K.; Tu, T.; Gottweis, J.; Sayres, R.; Wulczyn, E.; Amin, M.; Hou, L.; Clark, K.; Pfohl, S. R.; Cole-Lewis, H.; et al. 2025. Toward expert-level medical question answering with large language models. *Nature Medicine*, 1–8.

Smith, D. W. 2018. Phenomenology. In Zalta, E. N., ed., *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, Summer 2018 edition.

Song, I.; Pendse, S. R.; Kumar, N.; and De Choudhury, M. 2024. The typing cure: Experiences with large language model chatbots for mental health support. *arXiv preprint arXiv:2401.14362*.

Soon, Y. E.; Murray, C. M.; Aguilar, A.; and Boshoff, K. 2020. Consumer involvement in university education programs in the nursing, midwifery, and allied health professions: a systematic scoping review. *International Journal of Nursing Studies*, 109: 103619.

Spiegelberg, E. 2012. *The phenomenological movement: A historical introduction*, volume 5. Springer Science & Business Media.

Staff, M. 2016. In-Depth: How WebMD navigated the rise of digital health — mobihealthnews.com.

https://www.mobihealthnews.com/news/depth-how-webmd-navigated-rise-digital-health. [Accessed 19-05-2025].

Steinhardt, R. 2019. Perception and working memory are deeply entangled, study finds — medicalxpress.com. https://medicalxpress.com/news/2019-07-perception-memory-deeply-entangled.html. [Accessed 18-05-2025].

Tampubolon, M.; and Nadeak, B. 2024. Artificial Intelligence and Understanding of Religion: A Moral Perspective. *International Journal of Multicultural and Multireligious Understanding*, 11(8): 903–914.

Terry, M.; Kulkarni, C.; Wattenberg, M.; Dixon, L.; and Morris, M. R. 2023. Interactive AI alignment: specification, process, and evaluation alignment. *arXiv preprint arXiv:2311.00710*.

Theodoris, C. V.; Xiao, L.; Chopra, A.; Chaffin, M. D.; Al Sayed, Z. R.; Hill, M. C.; Mantineo, H.; Brydon, E. M.; Zeng, Z.; Liu, X. S.; et al. 2023. Transfer learning enables predictions in network biology. *Nature*, 618(7965): 616–624.

Tu, T.; Schaekermann, M.; Palepu, A.; Saab, K.; Freyberg, J.; Tanno, R.; Wang, A.; Li, B.; Amin, M.; Cheng, Y.; et al. 2025. Towards conversational diagnostic artificial intelligence. *Nature*, 1–9.

Turchin, A. 2019. AI alignment problem:"human values" don't actually exist. *arXiv*.

Umbrello, S.; and De Bellis, A. F. 2018. A value-sensitive design approach to intelligent agents. In *Artificial intelligence safety and security*, 395–409. Chapman and Hall/CRC.

van der Maden, W.; Lomas, D.; and Hekkert, P. 2023. A framework for designing AI systems that support community wellbeing. *Frontiers in Psychology*, 13: 1011883.

Wade, S. E.; and Reynolds, R. E. 1989. Developing metacognitive awareness. *Journal of reading*, 33(1): 6–14.

Walsh, J.; and Boyle, J. 2009. Improving acute psychiatric hospital services according to inpatient experiences. A user-led piece of research as a means to empowerment. *Issues in mental health nursing*, 30(1): 31–38.

Wang, D.; Kohler, C.; ten Pas, A.; Wilkinson, A.; Liu, M.; Yanco, H.; and Platt, R. 2019. Towards assistive robotic pick and place in open world environments. In *The International Symposium of Robotics Research*, 360–375. Springer.

Whalley, J. L.; Lister, R.; Thompson, E.; Clear, T.; Robbins, P.; Ajith Kumar, P.; and Prasad, C. 2006. An Australasian study of reading and comprehension skills in novice programmers, using the Bloom and SOLO taxonomies. In *Conferences in Research and Practice in Information Technology Series*.

Williams, C. Y.; Zack, T.; Miao, B. Y.; Sushil, M.; Wang, M.; Kornblith, A. E.; and Butte, A. J. 2024. Use of a large language model to assess clinical acuity of adults in the emergency department. *JAMA Network Open*, 7(5): e248895–e248895.

Yang, Y.; Liu, X.; Jin, Q.; Huang, F.; and Lu, Z. 2024. Unmasking and quantifying racial bias of large language models in medical report generation. *Communications Medicine*, 4(1): 176.

Yao, D. W. J. 2024. The role of artificial intelligence in shaping religion and social studies. *Convergence Chronicles*, 5(1): 334–342.

Zainuddin, N. 2024. Does Artificial Intelligence Cause More Harm than Good in Schools? *International Journal of Language Education and Applied Linguistics*, 14(1): 1–3.

Ziewitz, M.; and Singh, R. 2021. Critical companionship: Some sensibilities for studying the lived experience of data subjects. *Big Data & Society*, 8(2): 20539517211061122.

Çağın Zort; Karabacak, E.; Şevket Öznur; and Dağlı, G. 2023. Sharing of cultural values and heritage through storytelling in the digital age. *Frontiers in Psychology*, 14. Section: Educational Psychology.