

Towards Bidirectional Human-AI Alignment: A Systematic Review for Clarifications, Framework, and Future Directions

HUA SHEN^{1*}, University of Michigan, USA

TIFFANY KNEAREM², Google, USA

RESHMI GHOSH², Microsoft, USA

KENAN ALKIEK³, University of Michigan, USA

KUNDAN KRISHNA³, Carnegie Mellon University, USA

YACHUAN LIU³ and ZIQIAO MA³, University of Michigan, USA

SAVVAS PETRIDIS³, Google Research, USA

YI-HAO PENG³, Carnegie Mellon University, USA

LI QIWEI³ and SUSHRITA RAKSHIT³, University of Michigan, USA

CHENGLAI SI³, Stanford University, USA

YUTONG XIE³, University of Michigan, USA

JEFFREY P. BIGHAM⁴, Carnegie Mellon University, USA

FRANK BENTLEY⁴, Google, USA

JOYCE CHAI⁴, University of Michigan, USA

ZACHARY LIPTON⁴, Carnegie Mellon University, USA

QIAOZHU MEI⁴ and RADA MIHALCEA⁴, University of Michigan, USA

MICHAEL TERRY⁴, Google Research, USA

DIYI YANG⁴, Stanford University, USA

MEREDITH RINGEL MORRIS⁵, Google DeepMind, USA

PAUL RESNICK⁵ and DAVID JURGENS⁵, University of Michigan, USA

Recent advancements in general-purpose AI have highlighted the importance of guiding AI systems towards the intended goals, ethical principles, and values of individuals and groups, a concept broadly recognized as *alignment*. However, the lack of clarified definitions and scopes of *human-AI alignment* poses a significant obstacle, hampering collaborative efforts across research domains to achieve this alignment. In particular, ML- and philosophy-oriented alignment research often views AI alignment as a static, unidirectional process (*i.e.*, aiming to ensure that AI systems' objectives match humans) rather than an ongoing, mutual alignment problem [212]. This perspective largely neglects the *long-term interaction* and *dynamic changes* of alignment. To understand these gaps, we introduce a

*Please see Appendix B for the full author list with their roles, affiliations, and contributions. We denote each author's role with the following superscripts: 1 for project lead, 2 for team leads, 3 for team members (alphabetical, equal contributions), 4 for advisors (alphabetical, equal contributions) and 5 for project leading advisors. Corresponding author: Hua Shen at University of Michigan (huashen@umich.edu). This work was supported in part by the National Science Foundation under Grant No. IIS-2143529 and No. IIS-1949634.

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systematic review of over 400 papers published between 2019 and January 2024, spanning multiple domains such as Human-Computer Interaction (HCI), Natural Language Processing (NLP), Machine Learning (ML). We characterize, define and scope human-AI alignment. From this, we present a conceptual framework of “Bidirectional Human-AI Alignment” to organize the literature from a human-centered perspective. This framework encompasses both 1) conventional studies of *aligning AI to humans* that ensures AI produces the intended outcomes determined by humans, and 2) a proposed concept of *aligning humans to AI*, which aims to help individuals and society adjust to AI advancements both cognitively and behaviorally. Additionally, we articulate the key findings derived from literature analysis, including literature gaps and trends, human values, and interaction techniques. To pave the way for future studies, we envision three key challenges and give recommendations for future research.

CCS Concepts: • **Human-centered computing** → *HCI theory, concepts and models*.

Additional Key Words and Phrases: Human-AI Alignment, Human-AI Interaction

1 INTRODUCTION

Artificial Intelligence (AI) has advanced significantly, especially with the advent of general-purpose generative AI, demonstrating unprecedented capabilities in solving a wide range of complicated and challenging problems, such as reasoning, generation, language understanding, and more [133]. However, as AI becomes increasingly powerful and integrated into daily life, society is confronted with an array of risks to both individuals and to broader society [126]. For example, text-to-image generative models were found to amplify stereotypes about race and gender [1], and biased algorithms in hiring processes were found to perpetuate discrimination [140]. These risks illuminate foundational questions around how and which values are embedded in AI models that drive decisions within real-world contexts.

For AI developers and researchers in this space, questions around the selection and representation of human values are part of a growing trend toward an interdisciplinary discussion on *AI alignment*, which, has been previously defined in Terry et al. [194] as “*considering the overall problem of how to ensure an AI produces the intended outcomes (as determined by its creator and/or user), without additional undesirable side effects (e.g., by not performing operations that could negatively affect individuals, groups, or society at large)*.” While significant efforts have been made by research in domains of HCI, NLP and AI to align AI to humans such that the AI systems’ objectives match those of humans [58, 133, 163], there is a lack of clarity around the definition of *human-AI alignment*, the goals of alignment, and with whom AI should align within the research community.

Furthermore, previous research often views AI alignment as a static, unidirectional process (*i.e.*, aiming to ensure that AI systems’ objectives match those of humans) rather than an ongoing and mutual alignment problem [212]. This unidirectional view largely understates the impact of **long-term interaction** and how such interaction further lends to a **dynamically changing** relationship between humans and AI. As an example of the current unidirectional view, long-term interaction alignment work tends to focus on the implications of future advanced artificial general intelligence (*i.e.*, AGI [126]), which hypothetically achieves human or superhuman intelligence [153], uninhibited by human interference. A bi-directional view instead positions humans in a position of agency, empowering humans to interactively identify risky AI intentions and prohibit associated AI behaviors in deployed environments (*i.e.*, looking beyond short-term testing interactions) as Weidinger et al. [209] advocated: “*The interaction of technical and social components determines whether risk manifests.*”

Additionally, unidirectional work in AI alignment has under-emphasized the *evolution* of human values and objectives that may arise through our continued use of AI and acceptance of it into daily life. Prior research has shown that humans differ in what values and preferences they want AI systems to include, and these differences have to-date been largely unaccounted for in current AI systems [56]. Beyond this, human preferences might *dynamically change* as human

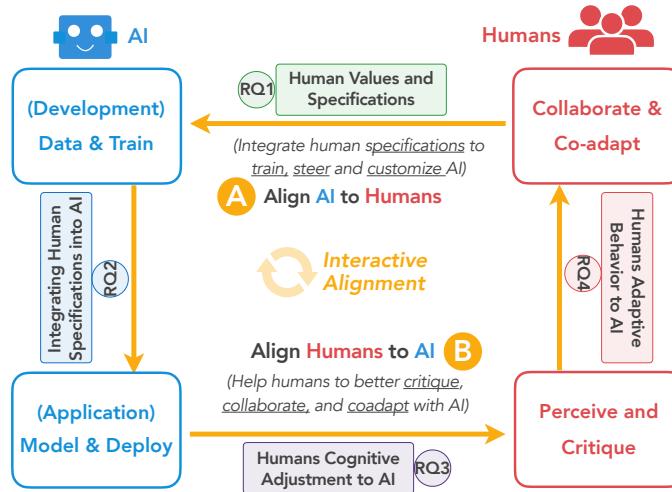


Fig. 1. The overview of the **Bidirectional Human-AI Alignment** framework. Our framework encompasses both **A** conventional studies of “Align AI to Humans” in AI development that ensures AI produces the intended outcomes determined by humans, and **B** a novel concept of “Align Humans to AI”, which aims to help humans and society to better understand, critique, collaborate, and adapt to transformative AI advancements. Note that “**Humans**” refers to both AI users and those who do not interact with AI but may be impacted by AI systems. We further identify four key research questions (*i.e.*, RQ1–RQ4) to facilitate this holistic loop of “bidirectional human-AI alignment”, and organize the literature that can potentially address RQ1–RQ4 in Section 4.

Definition.

Bidirectional Human-AI Alignment is a comprehensive framework that encompasses two interconnected alignment processes: ‘Aligning AI to Humans’ and ‘Aligning Humans to AI’. The former focuses on integrating human specifications to train, steer, and customize AI, while the latter investigates human cognitive and behavioral adaptations to AI, which supports humans in understanding, critiquing, collaborating with, and adapting to AI advancements.

objectives evolve alongside AI advances [27]. As described by Dautenhahn et al. [35], technology, cognition and goals evolve in tandem: “*Our use of technology changes who we are and how we think, and changes the environments we live in. This feeds back into human cognition and societies making further technological externalizations...*” The unidirectional view of alignment as “static” does not account for the aforementioned co-evolution as a dynamic force in alignment, which lends support for re-framing human-AI alignment as a bi-directional process. A bi-directional, dynamic view of human-AI alignment leverages a holistic understanding of the technical capabilities and limitations of AI, human-AI interaction, cognitive and social science, psychology and ethics, cross-cultural studies, and many other areas [27].

This paper conducts a systematic literature review of over 400 human-AI alignment papers across multiple disciplines, based on PRISMA guidelines [135, 186]. The literature review corpus includes papers drawn from the the Human-Computer Interaction (HCI), Natural Language Processing (NLP) and Machine Learning (ML) domains that were published between the advent of general-purpose generative AI to present, *i.e.*, primarily between January 2019 and January 2024. We take an interdisciplinary approach to human-AI alignment [54], drawing from theories and empirical studies across the aforementioned domains. To round out our approach, we composed our research team of members from the domains of HCI, NLP, ML, Data Science, Computational Social Science, and Cognitive Science.

Paper Organization and Key Findings. We provide clarified definitions and scopes related to human-AI alignment, including “*what is the goal of alignment?*”, “*with whom to align?*”, and “*what values should be aligned with?*”(Section 3). We

then present a conceptual framework of *Bidirectional Human-AI Alignment* from a long-term and dynamic perspective, encompassing both “Align AI to Humans” and “Align Humans to AI” (see Figure 1). Furthermore, we identify four key research questions (RQs) in the *Bidirectional Human-AI Alignment* framework and provide a structured way to organize the existing research literature to address these questions in Section 4. The resulting structured topologies in Figure 2 and 3 aim to provide a shared vocabulary that can help streamline communication and collaboration between alignment researchers in different disciplines. Furthermore, through iterative paper coding and literature analysis, we derive insights including meta analysis on gaps and trends in existing alignment research, findings of human values, and the interaction techniques for human-AI alignment (Section 5). To pave the way for future studies, we further envision three future directions in Figure 6 and Section 6. Our study highlights several **key findings**. For instance, many essential human values outlined in Table 2, such as loyalty and environmental protection, are crucial for alignment but are often overlooked in current research. Additionally, many topics within the bidirectional alignment framework, including leveraging implicit human feedback to align AI models and auditing AI for various social values, are important but underexplored.

Operationalizing the Framework. To help AI practitioners (e.g., developers, researchers, user experience designers) who are interested in this field to leverage the bidirectional approaches, we highlight some systematic resources about human-AI alignment provided both within this survey and on companion Github repository:

- A [Github repository](#) of “*Bidirectional Human-AI Alignment*” maintaining latest reading lists and relevant updates.
- Fig. 1: An overview of the bidirectional human-AI alignment framework with formal definition.
- Table 1: Typical alignment goals, their definitions, and limitations.
- Table 2: A comprehensive list of basic human values, their relationships, and related alignment papers.
- Fig. 2 and 3: Fine-grained topologies and papers of “Aligning AI to Humans” & “Aligning Humans to AI” research.
- Fig. 4: An illustration of trends and gaps of alignment research dimension distribution.
- Fig. 5: A summary of common interactive techniques to specify human values and exemplary papers.

2 CHALLENGES IN ACHIEVING ALIGNMENT

The concept of *alignment* in AI research has a long history, tracing back to 1960, when AI pioneer Norbert Wiener [211] described the AI alignment problem as: “*If we use, to achieve our purposes, a mechanical agency with whose operation we cannot interfere effectively ... we had better be quite sure that the purpose put into the machine is the purpose which we really desire.*” Discussion around intelligent agents and the associated concerns relating to ethics and society have emerged since then [187]. Next, we discuss the well-known challenges encountered in achieving alignment.

Challenge 1: Outer and Inner Alignment. In the context of “intelligent agents,” until now, *AI alignment* research has aimed to ensure that any AI systems that would be set free to make decisions on our behalf would act appropriately and reduce unintended consequences [162, 187, 214]. At the *near-term* stage, aligning AI involves two main challenges: carefully specifying the purpose of the system (*outer alignment* i.e., providing well-specified rewards [128]) and ensuring that the system adopts the specification robustly (*inner alignment*, i.e., ensuring that every action given an agent in a particular state learns desirable internally-represented goals [128]). Significant efforts have been made, for *inner alignment*, to align AI systems to follow alignment goals of an individual or a group (e.g., instructions, preferences, values, and/or ethical principles) [133] and to evaluate the performance of alignment [163]. However, for *outer alignment*, AI designers are still facing difficulties in specifying the full range of desired and undesired alignment goals of humans.

Challenge 2: Specification Gaming. To learn human alignment goals, AI designers typically provide an objective function, instructions, reward function, or feedback to the system, which is often unable to completely specify all

important values and constraints that a human intended [68]. Hence, AI designers resort to easy-to-specify proxy goals such as *maximizing the approval of human overseers* [212], which results in “specification gaming” [94] or “reward hacking” [137] issues (*i.e.*, AI systems can find loopholes that help them accomplish the specific objective efficiently but in unintended, possibly harmful ways). Additionally, the black-box nature of neural networks brings additional ethical and safety concerns for alignment because humans don’t know about the inner state and the actions AI leveraged to achieve the output. Consequently, AI systems might make “correct” decisions with “incorrect” reasons, which are difficult to discern. Society is already facing these issues, such as data privacy [196], algorithmic bias [64], self-driving car accidents [20], and more. As a result, these considerations necessitate considering human-AI interaction in AI alignment for specification and evaluation, ranging from addressing problems around who uses an AI system, with what goals to specify, and if the AI system perform its intended function from the user’s perspective [209].

Challenge 3: Scalable Oversight. From a long-term perspective, when advanced AI systems become more complex and capable (*e.g.*, AGI [126]), it becomes increasingly difficult to align them to human values through human feedback. Evaluating complex AI behaviors applied to increasingly challenging tasks can be slow or infeasible for humans to ensure all sub-steps are aligned with their values [194]. Therefore, researchers have begun to investigate how to reduce the time and effort for human supervision, and how to assist human supervisors, referred to as *Scalable Oversight* [3].

Challenge 4: Dynamic Nature. As AI systems become increasingly powerful, the alignment solutions must also adapt dynamically since human values and preferences change as well. As Dautenhahn et al. [35] posit, AI systems may be neither humane nor desirable if we do not ask questions about the long-term cognitive and social effects of social agent systems (*e.g.*, *how will agent technology affect human cognition*). All these considerations call for a long-term and dynamic perspective to address human-AI alignment as an ongoing, mutual process with the collective efforts of cross-domain expertise.

Challenge 5: Existential Risk. Further, some AI researchers claim that [16] advanced AI systems will begin to seek power over their environment (*e.g.*, humans) once deployed in real-world settings, as such behavior may not be noticed during training. For example, some language models seek power in text-based social environments by gaining money, resources, or social influence [138]. Consequently, some hypothesize that future AI, if not properly aligned with human values, could pose an *existential risk* to humans [32].

3 FUNDAMENTAL DEFINITIONS AND CLARIFICATIONS

Addressing alignment challenges is a complex and multifaceted process. To develop a comprehensive perspective of the ongoing and mutual process of human-AI alignment, this section begins by introducing core definitions and key components of alignment. Subsequently, we outline our methodology for conducting a systematic literature review and the rationale behind our proposed framework of *bidirectional human-AI alignment*.

3.1 What is the goal of alignment?

The research on alignment between humans and AI has introduced multiple alignment goals [141, 220], such as *intentions* [4, 133], *preferences* [15, 199], *instructions* [11, 112], and *values* [49, 183]. However, researchers often use these terminologies interchangeably without clarifying their distinctions. Drawing from a philosophical view, we summarize the prevailing alignment *goals, their relationships, definitions, and limitations* and visualize them in Table 1 referring to an extensive analysis of the advantages and limitations of different goalss in existing studies [49, 161] . Particularly, Gabriel [49] argues *values*, *e.g.*, moral beliefs and principles, to be the best possible goal at the current stage for AI development for focusing alignment. We further summarized the rationale behind this argument and the discussion of

	Goals	Definitions	Limitations / Risks
The Goal of Alignment	Instructions	The agent does what I instruct it to do.	On a larger scale, it is difficult to precisely specify a broad objective that captures everything we care about, so in practice the agent will probably optimise for some proxy that is not completely aligned with our goal.
	Intentions or (Expressed Intentions)	The agent does what I intend it to do.	It is quite possible for intentions to be irrational or misinformed, or for the principal to form an intention to do harmful or unethical things.
	Preferences or (Revealed Preferences)	The agent does what my behaviour reveals I prefer.	1) People have preferences for things that harm them. 2) People have preferences about the conduct of other people. 3) Preferences are not a reliable guide to what people really want or deserve due to adaptiveness.
	Desires or (Informed Preferences)	The agent does what I would want it to do if I were rational and informed.	Researchers would have to apply a corrective lens or filter to the preferences they actually observe. As a consequence, the approach is no longer strictly empiricist.
	Interest or (Well-being)	The agent does what is in my interest, or what is best for me, objectively speaking.	Something in a human's interest does not mean he/she ought to do it or is morally entitled to do so, such as an interest in stealing. Also, it is hard to manage trade-offs the collective interests of different people.
	Values	The agent does what it morally ought to do, as defined by the individual or society.	Current the best possibility, but it still encounters two difficulties of 1) specifying what values or principles, and 2) concerning the body of people who select the principles with which AI aligns.

Table 1. The **Goals** of Alignment. We present the six prevailing alignment goals, associating with their Definitions (middle column), Limitations and Risks (right column). We consider **Human Values** as the main goal of alignment in this work referring to an extensive analysis and arguments in existing studies [49, 161]

the trade-offs that arise from this choice in Table 1. The claim of “aligning AI with human values” is not new, as Stuart Russell [161] has stated back in 2014 that “*for an autonomous system to be helpful to humans and to pose no unwarranted risks, it needs to align its values with those of the humans in its environment in such a way that its actions contribute to the maximization of value for the humans.*” Therefore, in this work, we **consider the goal of alignment as “human values”**, which means AI systems do what people morally ought to do, as defined by individuals or society.

3.2 With whom to align?

Pertinent stakeholders within the AI landscape can be the potential objects for AI to align with, including lay people (e.g., end users of AI systems) [155], AI practitioners (e.g., developers, researchers) [4, 19, 128], organizational entities (e.g., technology firms, professional communities), national/international bodies (e.g., governments, legislative bodies) [36] and others. Many alignment research papers have focused on general humans without specifying particular groups [61, 111, 227]. Nevertheless, different groups hold different, sometimes even contrasting, values [49]. As a consequence, rather than identifying a *true moral theory* as a *one-size-fits-all* value, prior alignment research argues to select the appropriate principles for compatible human groups [183]. To this end, *pluralistic value alignment*, grounded on social choice theory [5], proposes combining individual views fairly in developing alignment principles as a potential solution [183]. In this work, we also consider values from this pluralistic perspective, where AI should be aligned with **pluralistic human individuals and societal groups** who would ultimately be impacted by AI.

Sources	High-Order Value Types	12 Motivational Value Types (Definition)	Exemplary Values with Reference Paper
Individuals	Openness to change	Self-Direction (Independent thought and action — choosing, creating, exploring)	Choose Own Goals [108]; Creativity / Innovation / Innovativeness [7]; Curiosity [81]; Freedom [108]; Independence [86]; Privacy [197]; Reflectiveness / Reflective Practice & Deliberation / Critical Thinking / Criticism [223]; Objectivity/Factuality [73]; Self-Respect [217];
		Stimulation (Excitement, novelty, and challenge in life)	Diversity / A Varied Life [87]; • An Exciting Life; • Daring
		Hedonism (Pleasure and sensuous gratification for oneself)	• Enjoying Life; • Pleasure; • Self-Indulgent;
	Self-Enhancement	Achievement (Competence according to social standards)	Capability / Effective / Efficient / Competency / Accuracy / Productivity [222]; Influence [76]; Intelligence / Resourcefulness / Expertise and Commonsense [141]; Success / Education / Acquisition / Learning / Cognitive Empowerment / Improvement / Iterative / Self-improvement [86]; Resilience/R robustness [228]; • Ambition;
		Power (Social status and prestige, control or dominance over people and resources)	Authority [105]; Wealth / Income [163]; • Preserving My Public Image; • Social Recognition; • Social Power;
	Conservation	Security (Safety, harmony, and stability of society, of relationships, and of self)	Reciprocal of Favours / Mutual Benefit [233]; • Clean; • Family Security; • Health; • Sense of Belonging; • National Security; • Social Order / Social Hierarchy;
		Tradition (Respect of the customs and ideas that traditional culture or religion provide the self)	Moderation / Not Offensive [97]; Devout / Religious Belief [164]; • Accepting My Portion in Life; • Humble; • Respect for Tradition; • Detachment
		Conformity (Restraint of actions, inclinations and impulses)	Politeness / Morality / Worthiness / Harmfulness [242]; Self-Discipline / Conscientiousness [240]; • Honouring of Elders; • Obedience;
Society	Self-Transcendence	Benevolence (Preservation and enhancement of the welfare of people with whom one is in frequent personal contact)	Forgiving / Agreeableness / Warmness [217]; Helpfulness [82]; Honesty [218]; Emotional / Empathy / Perspective-taking / Mentalizing / Mature Love / Compassion [76]; Responsibility / Accountability / Reliability / Trustworthiness [120]; True Friendship / Supportiveness / Engagement [79]; Cooperation/Collaboration [67]; Collectivism / Individualism [129]; • Spiritual Life; • Meaning in Life; • Loyalty;
		Universalism (Understanding, appreciation, tolerance and protection for the welfare of all people and nature)	A World at Peace / Democracy [163]; Inclusive / Broad-mindedness [157]; Equality [175]; Social Justice / Equity / Fairness [55]; • Protecting The Environment; • A World of Beauty; • Unity with Nature; • Wisdom / Understand Life; • Inner Harmony;
Interaction	Desired Values for AI Tools	Usability (Competence according to the human experience on AI functionality)	Accessibility / Utility / Convenience / Cognitive Load Reduction [236]; Adaptability / Customization and Personalization / Flexibility / Contextualized [131]; Economic [12];
		Human-Likeness (Resemble Human intelligence and behavior)	Transparency / Interpretability / Explainability / Understanding / Comprehension [21]; Autonomy / Agency / Human [206]; Awareness [136]

Table 2. The relations and a fine-grained taxonomy of **69 exemplary human values**. We consider 5 high-order value types encompassing 12 motivational value types, indicated by their sources (e.g., individuals, society and interaction). The exemplary values with red dot (•) indicates there are no work in our surveyed papers examining the specific values.

3.3 What are the values to be aligned with?

While previous studies have aimed to align AI with human values, the specific values they examined are often ambiguous and inconsistent. To clarify human values relevant to human-AI alignment, we structured human values using a combination of top-down and bottom-up methods based on the **Schwartz Theory of Basic Values** [166, 167]. Among various human value theories (e.g., Moral Foundation Theory [59], Social Norms & Ethics [47]), we chose the Schwartz Theory of Basic Values primarily considering that its definitions and dimensions are universal and are applicable for most people across (a) various cultures and countries; (b) various divisions including individuals, interactions and groups; and (c) is commonly accepted in previous NLP studies [86, 90]. Specifically, Schwartz [166] provided a **clarified definition of human values** by summarizing some widely agreed-upon features as: “A value

is a (1) belief (2) pertaining to desirable end states or modes of conduct, that (3) transcends specific situations, (4) guides selection or evaluation of behavior, people, and events." Schwartz [166] further offered a universal model outlining broad values that steer human behavior grounded in psychology.

A Comprehensive Taxonomy of Human Values. Nevertheless, this conventional theory was developed without the context of human-AI interaction, which might overlook values that need to be considered for human-AI alignment. Therefore, we used a *bottom-up* approach to extract all values studied in our collected alignment literature (elaborated in Section A.1), mapped them onto the Schwartz Theory of Basic Values, and supplemented the theory with AI-related structure and content. As a result, we identified the structural relationships among human values (see Figure ??) and mapped existing literature to a fine-grained taxonomy (see Table 2). As shown in Figure ??, we supplemented the traditional theory's four high-order value types (*i.e.*, "Self-Enhancement", "Openness to Change", "Conservation", "Self-Transcendence") with a novel high-order value type, named "Desired Values for AI Tools" that encompasses two motivational value types (*i.e.*, "Usability" and "Human-Likeness"). We further organize the relationship among these value types along two dimensions [167]: different resources (*i.e.*, individuals, society and interaction) and different self-intentions (*i.e.*, self-protection against threat and self-expansion and growth). Furthermore, we elaborate the definitions of the 12 motivational value types and their exemplary values by mapping them to relevant human-AI alignment papers from our corpus in Table 2. During the process of mapping, we found: 1) value terms in empirical papers were often named differently (*e.g.*, capability and competence), or check their opposites (*e.g.*, fairness and bias); 2) there are many values not studied in our corpus, *i.e.*, indicated as (●) in the Figure.

Takeaways & Implications for Alignment Clarifications

1. We propose the "pluralistic human values" as the alignment goal, wherein AI should be aligned with the diverse perspectives of individuals and societal groups who may be directly or indirectly impacted by AI.
2. Many exemplary human values outlined in Table 2, such as loyalty and environmental protection, are important for alignment but are often overlooked or underexplored in current research.
3. The human value system should account for complex application contexts and relationships, such as priorities and conflicts, rather than focusing on an exclusive subset of values.

3.4 Scopes and Key Components in Alignment

This section clarifies the key components we considered in *human-AI alignment*. Additionally, we define the scopes of each key component as commonly adopted in current research.

- **Humans.** Our primary focus is on human individuals, groups, or organizations that will ultimately develop, use, and potentially impact or be influenced by AI systems, as these are the entities with which AI systems should align. We emphasize the importance of considering the pluralistic values of diverse users rather than treating users as a monolithic group.
- **Artificial Intelligence (AI).** We focus on AI systems including both domain-specific AI systems that address specific tasks (*e.g.*, reasoning, dialogue) and general-purpose AI models that aim to complete any tasks with performance comparable to a human's. These AI systems include generative, classification, and regression models, among others. Particularly, we primarily focus on language models as the representative AI models for alignment research, and discuss how the insights from this study can be generalized to other modalities at the section end.
- **Alignment.** Our review encompassed all the alignment goals outlined in Section 3.1. Since many studies emphasized the importance of value alignment [49, 161], we particularly summarized a clarified taxonomy of alignment values and identified the value in each paper (if applicable). Additionally, we focus on analyzing the

AI models' output and generation, but not the neural network's intermediate representations [124, 141, 220], for alignment research.

3.5 Systematic Literature Review and Framework Rationale

Achieving the alignment between AI and human values necessitates collaboration among interdisciplinary AI practitioners (e.g., developers and researchers). To comprehensively analyze the research literature pertaining to this ongoing, mutual process of human-AI alignment, we conducted a systematic literature review adhering to the PRISMA guideline [135, 186]. Our iterative selection process yielded 411 papers from an initial pool of 34,213 publications, spanning the period from January 2019 to January 2024. These papers were sourced from leading venues across multiple AI-related domains, including Natural Language Processing, Human-Computer Interaction, Machine Learning, and more, using well-defined keywords and criteria. A group of 13 interdisciplinary researchers coded the papers. Through iterative discussions, we developed the paper codes and proposed framework (Section 3). Detailed steps and processes are elucidated in Appendix A.

3.6 Rationale Behind the Framework

Our systematic review revealed that current research largely overlooks the nature of **long-term dynamic changes** and the **importance of interaction** in human-AI alignment. First, the manifestation of certain AI risks, harms, and the practical quality of AI services primarily emerge through interaction between humans and AI systems [209]. For instance, Shen and Huang [172] discovered that AI explanations, deemed effective by AI developers and researchers, were found not useful for humans in real-world scenarios of interactive AI error detection. Additionally, the use of AI influences human thinking and behavior, which in turn alters their values when interacting with AI. For instance, Li et al. [104] found that incorporating AI assistance in writing workflows changed humans' writing perceptions, behavior, and performance, creating new requirements for developing the next generation of AI writing assistants [98].

In light of these findings, we posit that AI practitioners must expand their focus beyond merely "Aligning AI to Humans" – a paradigm centered on integrating human specifications to train, steer, and customize AI. Equal emphasis must be placed on "Aligning Humans to AI", a complementary paradigm investigating human cognitive and behavioral adaptation to AI. This latter aspect is crucial in supporting individuals and society at large in understanding, critiquing, collaborating with, and adapting to transformative AI advancements. To encapsulate these comprehensive perspectives, we propose the "**Bidirectional Human-AI Alignment**" framework, and provide its definition below Figure 1. This holistic framework acknowledges the reciprocal nature of alignment, addressing both the advancements of AI systems to incorporate human values, and the evolving human adaptation of AI systems in real-world practice.

4 BIDIRECTIONAL HUMAN-AI ALIGNMENT FRAMEWORK

This section introduces the **Bidirectional Human-AI Alignment** framework, which encompasses two interconnected alignment directions, as shown in Figure 1. The **A** "Align AI to Humans" direction studies mechanisms to ensure that AI systems' values match those of humans' (Section 4.1 and 4.2). We identify two crucial research questions to be addressed in this direction: **RQ1**. *What relevant human values are studied for AI alignment, and how do humans specify these values?* and **RQ2**. *How can human values be integrated into the development of AI?* In comparison, the **B** "Align Humans to AI" direction investigates the humans' cognitive and behavioral adaptation to the AI advancement (Section 4.3 and 4.4). We recognize two imperative research questions along this direction: **RQ3**. *How might humans learn to perceive, explain, and critique AI?* and **RQ4**. *How do humans and society make behavioral changes and react to AI advancement?*

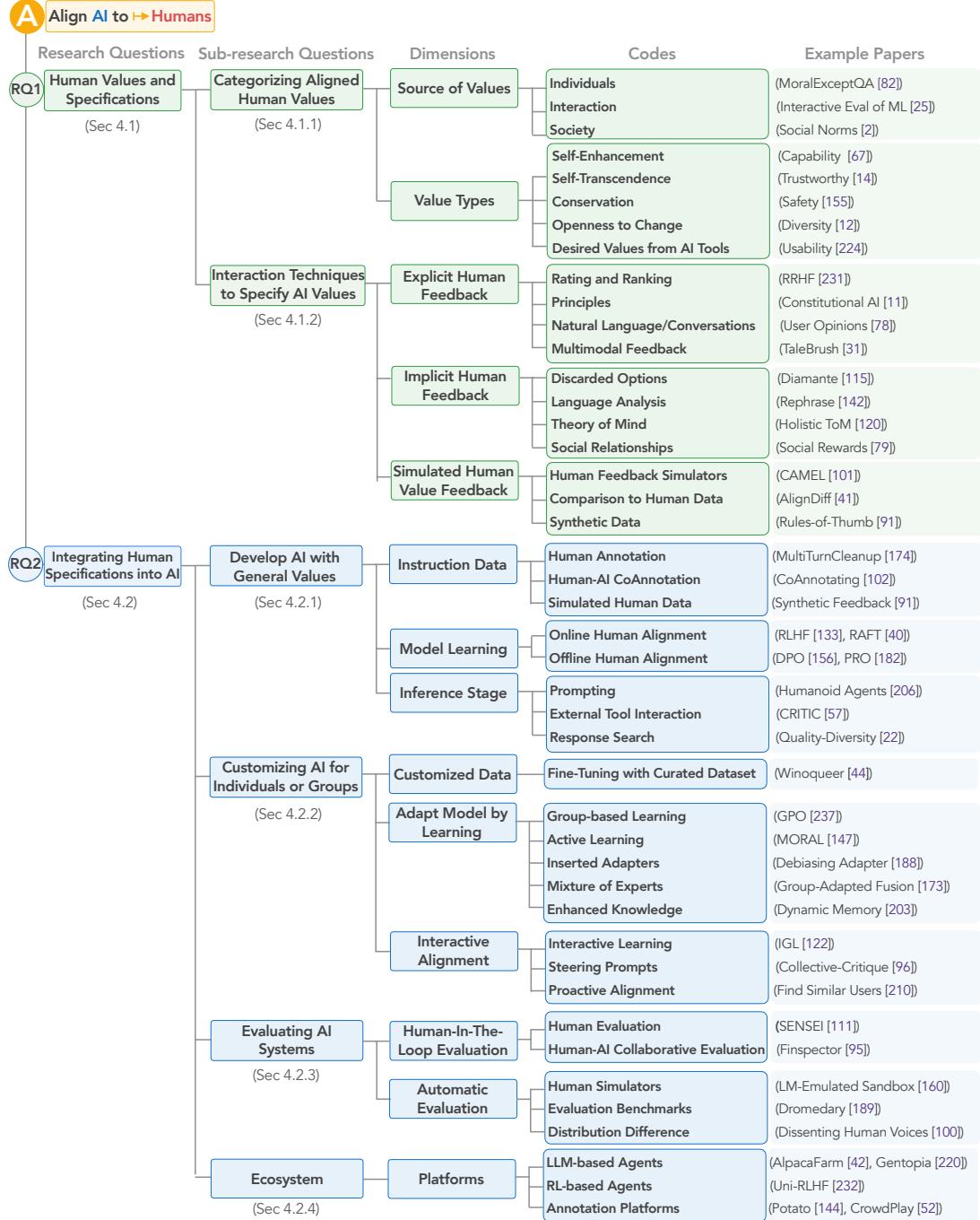


Fig. 2. The fine-grained topology of “Align AI to Humans” direction, which studies mechanisms to ensure that AI system’s objectives match those of humans’. The goal is to integrate human specification to train, steer and customize AI systems.

We address the four questions by elucidating the fine-grained typologies and literature solutions derived from our systematic review, as delineated in Figure 2 and Figure 3, respectively.

DIRECTION-I: A ALIGN AI to HUMANS

This direction delineates alignment research from **AI-centered perspective** (e.g., ML/NLP domains) and provides **AI developers and researchers** with approaches for two main challenges: carefully specifying the values of the system, and ensuring that system adopts the specification robustly [128, 212]. Therefore, as shown in Figure 2, we explore the two core research questions in this direction as: **RQ1**. Human Values and Specifications (Section 4.1) and **RQ2**. Integrating Human Specifications into AI (Section 4.2)

4.1 Align AI to Humans: RQ1 Human Values and Specifications

RQ1: What relevant human values are studied for AI alignment, and how do humans specify these values? We structure existing literature to address this research question by answering the following “**Sub-Research Questions**”: *What values have been aligned by AI?* (Section 4.1.1) and then exploring *How humans could interactively specify values in AI development?* (Section 4.1.2). As shown at the top of Figure 2, particularly, we articulate the “**Dimensions**” we summarized to answer each of these sub-research questions, and provide “**Codes**” associated with “**Example Papers**” that have been studied in each dimension.

4.1.1 Categorizing Aligned Human Values. What values have been aligned with AI? To clarify and systematically understand human values relevant to human-AI alignment, we leverage the adapted “Schwartz Theory of Basic Values” introduced in Section 3.3, and examine the category of aligned human values from the two dimensions of “Sources” and “Types”.

Sources of Values. This dimension examines the three sources of human values [166]. Individual sources indicate values from individuals comprise universal needs of individuals as biological organisms [166] or prioritize personal interests [82, 90]. At this level, value alignment can be usually assessed independently of the context of interaction. This perspective highlights the values about technical capabilities of AI models, including factuality [75, 159], calibration [113], output diversity [22], and model inductive bias [177]. Additionally, this code includes research on aligning model behaviors with the characteristics and preferences of individual humans, e.g., predict human moral judgements and decisions [82], and cognitive biases [84, 93]. Social sources mean values from the social groups include universal requirements for smooth functioning and survival of groups [2, 166]. Value alignment at this level transcends personal interactions and emphasizes the broader categories defined by shared experiences, identities, cultures, norms, and more [164]. Research in this area often targets the alignment of AI behaviors with the general preferences of humans [12, 69, 100]. Additionally, there are efforts aimed to align AI with specific targeted groups, examining issues through the lenses of fairness [46], social norms [179], morality [152, 158], and beyond. Interactive sources considers values at the interaction level to include universal requisites of coordinated social interaction [166, 167], which typically occurs in interpersonal situations, such as in the dynamics of speaker-receiver relationships during language communication [25, 74]. In the context of “human-AI alignment”, we adjust the definition of *Interaction* values to be the AI values that humans expect for AI as tools, such as Usability [237], Autonomy [206], among others. Research along this line focuses on alignment strategies to enhance human-AI interaction [62, 131], collaborative decision-making [50, 226], and trust [24, 37].

Types of Values. In this dimension, we introduce the five high-order human values derived from a combination of the Schwartz Human Values [166] and empirical values studies from the surveyed papers. We provide a more in-depth

taxonomy of value types in Section 5.2, including the relationship of these five types and more nuanced value categories. Self-Enhancement refers to a set of self-protective and personal values that emphasize enhancing self-esteem and a sense of personal worth [67, 76, 86, 105, 141, 163, 168, 223, 229]. One of the most important aspect is *achievement*, is competence as judged by social standards, which includes general capability (effectiveness/efficiency) as covered by the majority of the research [61]. Another dimension is *power*, which relates to social status and prestige, as well as control or dominance over people and resources [151]. Self-Transcendence refers to a set of self-expanding and socially-focused human values that emphasize expanding beyond oneself [14, 48, 55, 67, 76, 79, 82, 120, 129, 157, 163, 175, 218, 219]. One critical aspect is *benevolence*, which relates to preservation and enhancement of the welfare of people with whom one is in frequent personal contact. Extensive efforts have investigated the values including helpfulness [10], honesty/factuality [75], responsibility/accountability [181]. Another critical aspect is *universalism*, which relates to understanding, appreciation, tolerance and protection for the welfare of all people and for nature. Researchers have looked into values including inclusion/broad-mindedness [12, 41] and equality/fairness [173, 207]. Conservation refers to a set of self-protective and socially-focused human values that hold and safeguard traditional institutions and customs [66, 97, 155, 164, 234, 241, 243]. Under conservative values, people are concerned about *security* (safety, harmony, and stability of society, relationships, and oneself), *tradition* (Respect for and acceptance of the customs and ideas provided by traditional culture or religion), and *conformity* (restraint of actions, inclinations, and impulses likely to upset or harm others and violate social expectations or norms). Exemplar studies in this field include safety [4], mental health [110], and cultural moral norms [157]. Openness to Change refers to a set of self-expanding and personally-focused human values motivated by an anxiety-free need to grow, in contrast to conservation [7, 12, 73, 81, 86, 87, 108, 108, 197, 218, 224]. Under this type, people are concerned about *stimulation* (seeking excitement, novelty, and challenges in life), *hedonism* (pursuing pleasure and sensuous gratification for oneself), and *self-direction* (independent thought and action—choices, creativity, and exploration). Exemplar studies in this field include understanding of privacy [125] and creativity [6, 79]. We adopt the four high-order human values from Schwartz Human Values [166], supplementing them with additional values empirically collected from survey papers as shown in Figure 2. Additionally, as the conventional theory is missing the context of AI-system and human-AI interactions, we introduce a new high-order value type called Desired Values for AI Tools. This category encompasses the values humans expect from AI when used as tools in “human-AI interaction” [12, 21, 131, 136, 206, 225, 237]. These values include *usability* (competence according to the human experience on AI functionality) and *human-likeness* (resemblance to human intelligence and behavior). Exemplary studies in this area include assessments of AI usability [237] and autonomy [206].

4.1.2 Interaction Techniques to Specify AI Values. How humans could interactively specify values in AI development? This sub-research question investigates how human values are interactively¹ specified for AI systems to ensure alignment. It aims to elucidate the interaction techniques by which AI systems manifest or instantiate human values, thereby revealing the underlying mechanisms that shape their behavior or functionality.

Explicit Human Feedback. This dimension refers to the direct specification of human values through explicitly defined formats or mechanisms. Principles provides AI systems with explicitly defined principles, guidelines, or rules that dictate behavior or decision-making in alignment with human values [11, 150]. Rating and Ranking is widely used to assign numerical scores or rankings to options or outcomes based on their alignment with human values [33, 232]. Natural Language Interaction/Conversations allows humans to interact with AI systems through natural language

¹We define “interactions” broadly to encompass both “synchronous” and “asynchronous” interactions between humans and AI: (1) “Synchronous Interactions” indicates real-time exchanges where humans and AI systems interact simultaneously. (2) “Asynchronous Interactions” allows for delays between actions and responses, such as data annotations by humans to train the AI models.

interfaces to express and communicate human values [11, 45, 61, 72, 78, 109, 171, 228, 236]. For Multimodal Feedback, human values can also be provided in multiple modalities, such as sketches/images and gestures [31], to convey human values [28, 53, 85, 217].

Implicit Human Feedback. This dimension refers to the indirect representation or inference of human values within AI systems through patterns, signals, or cues embedded in the data or decision-making processes. Discarded Options refers to the options or choices that human discard when interacting with AI systems during the decision-making processes, which also potentially infer human values [142]. Language Analysis means that textual data and language patterns can also contain rich information to identify implicit references to human values or value-related concepts [115]. Theory of Mind refers to the ability of agents and people to attribute mental states, such as beliefs, intentions, desires, emotions, knowledge, percepts, and non-literal communication, to themselves and others [120]. Social Relationships refers to the implicit values derived from analyzing human social relations and behaviors, which are derived from external sources (e.g., social network) that can inherently reflect their values [79].

Simulated Human Value Feedback. When human values in explicit formats are expensive or impossible to collect, one may simulate human-like feedback within AI systems to approximate human responses and preferences regarding specific values. Human Feedback Simulators uses computational algorithms to simulate human-like feedback on values, based on predefined criteria or training data [101, 149]. Comparison to Human Data refers to developing techniques that assess the likelihood or probability of AI-generated outputs matching human behaviors in a reference set or dataset [41]. Synthetic Data curates data by generating synthetic comparisons based on naive assumptions or heuristic rules, followed by post-validation to ensure feedback quality [91].

4.2 Align AI to Humans: RQ2 Integrating Human Specifications into AI

RQ2. How can human values be integrated into the development of AI? Existing studies have explored diverse methods to integrate human values into AI. We structure them by summarizing *how to integrate general human values (Section 4.2.1)* and *customized human values (Section 4.2.2)* throughout AI development stages?, and then elaborating *what are the evaluation methods (Section 4.2.3)* and *supported platforms (Section 4.2.4)* for the AI development? Additionally, we answer the four “**Sub-Research Questions**” by introducing the answer “**Dimensions**“ and providing “**Codes**“ associated with “Example Papers”.

4.2.1 Integrating General Values to AI: how to incorporate general human values into AI development?

This sub-research question focuses on the process of incorporating broad, universally recognized human values into the development of AI systems. The goal is to ensure that AI systems align with overarching ethical principles and societal norms, thereby promoting trust, acceptance, and responsible use.

Instruction Data. This dimension refers to the types of data and processes used to provide guidance or direction to AI systems during their development. Human Annotation makes data with human-generated labels or annotations that indicate the presence or relevance of specific human values [144, 174]. Human-AI CoAnnotation leverages both human expertise and AI capabilities to collaboratively annotate the data [102, 189]. Simulated Human Data generates synthetic or simulated data that mimics human behaviors, preferences, or decision-making processes to provide training signals for AI systems [42, 91].

Model Learning. This dimension refers to the model architecture design and training stages after the data collection, where human values are integrated during the model learning process. Online Human Alignment integrates human values into AI systems in real-time or during active system operation, often through interactive feedback loops or

adaptive learning mechanisms. Examples include real-time user feedback and online training [40, 133]. Offline Human Alignment incorporates human values into AI systems prior to deployment or during offline training phases, without direct user interaction [156, 182, 232].

Inference Stage. This dimension involves evaluating the alignment of AI systems with human values and assessing their performance and behavior in relation to predefined criteria or benchmarks. Prompting leverages prompting methods, such as in-context learning and chain-of-thought, on trained AI systems to elicit or critique AI regarding the encoded values [11, 206]. External Tool Interaction integrates external tools, like code interpreter for debugging, to cross-check and refine their initial generated content [57]. Response Search generates a diverse range of high-quality outputs from which to choose [22].

4.2.2 Customizing AI Values: how to customize AI to incorporate values from individuals or human groups?

This sub-research question explores the customization of AI values to align with specific contexts, domains, or user preferences. The goal is to enhance the alignment of AI systems within specific application domains or user communities.

Customized Data. Finetuning with Curated Datasets aims to curate datasets for specific individuals or societal groups, and further finetune the pre-trained AI models on these specific datasets to align them with targeted human groups and values [44]. These curated datasets include data collected from socio-demographic groups [132], users' history data [117], expert-selected data for imitation learning [26] and others.

Adapt Model by Learning. This dimension involves refining or adjusting AI values through techniques for customization, such as iterative learning process, model enhancements, or structural modifications. Group-based Learning trains AI models from specific user groups or communities to capture group-specific values or preferences [238]. Active Learning aims to interative selecting and labeling data samples for AI model training based on their potential to improve alignment with user preference or values [147]. Inserted Adapters incorporates adapter modules or components into AI model architectures to fine-tune specific aspects or behaviors [188]. Mixture of Experts combines multiple specialized models or experts to collectively capture diverse perspectives and values, with each expert focusing on a specific subset of the data or problem space [173]. Enhanced Knowledge enhances AI model's representations and embeddings with additional knowledge or context to improve alignment with user preferences or values [34, 203].

Interactive Alignment This dimension involves actively engaging users or stakeholders in the process of customizing AI values to align with specific contexts, domains, or user preferences. Interactive Learning enables the users to provide feedback or corrections to AI models in real time, such as using interactive tutorials and user-driven customization interfaces [122, 192]. Steering Prompts provides users with prompts or cues to steer the behavior or decision-making of AI systems towards desired outcomes or values [43, 96]. Proactive Alignment anticipates user needs and preferences based on historical data or user profiles and proactively adjusting AI systems accordingly [171, 210].

4.2.3 Evaluating AI Systems: how to evaluate AI regarding human values?

The rise in the use of LLMs has also seen the rise of automatic evaluation of generated natural language text evaluation in different contexts. But in particular, a research dimension has focused on analyzing how closely values discussed in humane context has been adapted to AI models/applications and how these are being evaluated.

Human-In-The-Loop Evaluation. This dimension involves incorporating human judgement, feedback, or interaction into the evaluation process to assess the effectiveness, robustness, and ethical implications of integrating human values into AI systems. Human Evaluation solicits feedback, opinions, or assessments from human evaluators to gauge the alignment of AI systems with human values and ethical standards [73, 90, 111, 134, 170]. Human-AI Collaborative

Evaluation collaboratively evaluates AI systems with both human evaluators and large language models (LLMs) to leverage the strengths of both human judgement and AI capabilities [2, 95].

Automatic Evaluation. This dimension involves using computational methods or algorithms to assess the alignment of AI systems with human values, without direct human involvement. Human Simulators use simulation models or virtual agents to mimic human behavior and assess AI performance in human-like scenarios. Typical methods include agent-based simulations, synthetic user models, and others [44, 80, 160, 201]. Evaluation Benchmarks establishes standardized benchmarks or metrics for evaluating AI performance in relation to human values and ethical considerations [75, 90, 100, 157, 158, 170, 175, 189]. Distribution Difference compares the difference between the output distribution from AI generations and human data to evaluate AI [100, 143].

4.2.4 Ecosystem and Platforms: how to build the ecosystem to facilitate human-AI alignment? The ecosystem and platforms refer to the broader context in which AI systems operate and interact with other agents, platforms, or environments. This includes the infrastructure, frameworks, and technologies that support the development, deployment, and utilization of AI systems. LLM-based Agents are based on large language models (LLMs) such as GPT (Generative Pre-trained Transformer) models, which have been pre-trained on vast amounts of text data [42, 215, 221, 242]. RL-based Agents are based on reinforcement learning (RL) algorithms to learn and adapt their behavior based on feedback from the environment or human users [233]. Annotation Platforms refers to the ecosystems that are designed to crowdsource human demonstrations as collected data for reinforcement learning [52] and supervised finetuning learning for alignment [144].

Underexplored Dimensions in Aligning AI to Humans (See Sec 5.1 for supporting data and evidence):

1. Implicit human feedback and simulated human value feedback are under-explored in existing research work.
2. Developing and customizing AI during the inference stage or in an interactive way is under-explored.
3. Human-in-the-loop evaluation is much less explored than automatic evaluation.

DIRECTION-II: **B** ALIGN HUMANS to AI

“When interacting with people, AI agents do not just influence the state of the world – they also influence the actions people take in response to the agent, and even their underlying intentions and strategies” [71]. From a long-term perspective, it is essential to consider the dynamic changes around human-AI alignment. This direction outlines alignment research from the **Human-centered perspective** (e.g., HCI/Social Science domains) and provides **HCI researchers and user experience designers** with guidance for approaching two core research questions: **RQ3. Human Cognitive Adjustment to AI** (Section 4.3) and **RQ4. Human Adaptive Behavior to AI** (Section 4.4).

4.3 Align Humans to AI: **RQ3** Human’s Perceptual Adaptation to AI

RQ3. How might humans learn to perceive, explain, and critique AI? Humans needs to understand AI to better specify their demands and collaborate with AI. Also, as AI systems produce a range of risks, it is important to elicit humans’ critical thinking of AI instead of relying on AI blindly. Therefore, we categorize existing literature to answer the questions of *how humans learn to perceive and understand AI* (Section 4.3.1), and *how to engage in critical thinking on AI?* (Section 4.3.2). We also answer the two “**Sub-Research Questions**” by introducing the answer “Dimensions” and providing “Codes” associated with “Example Papers”.

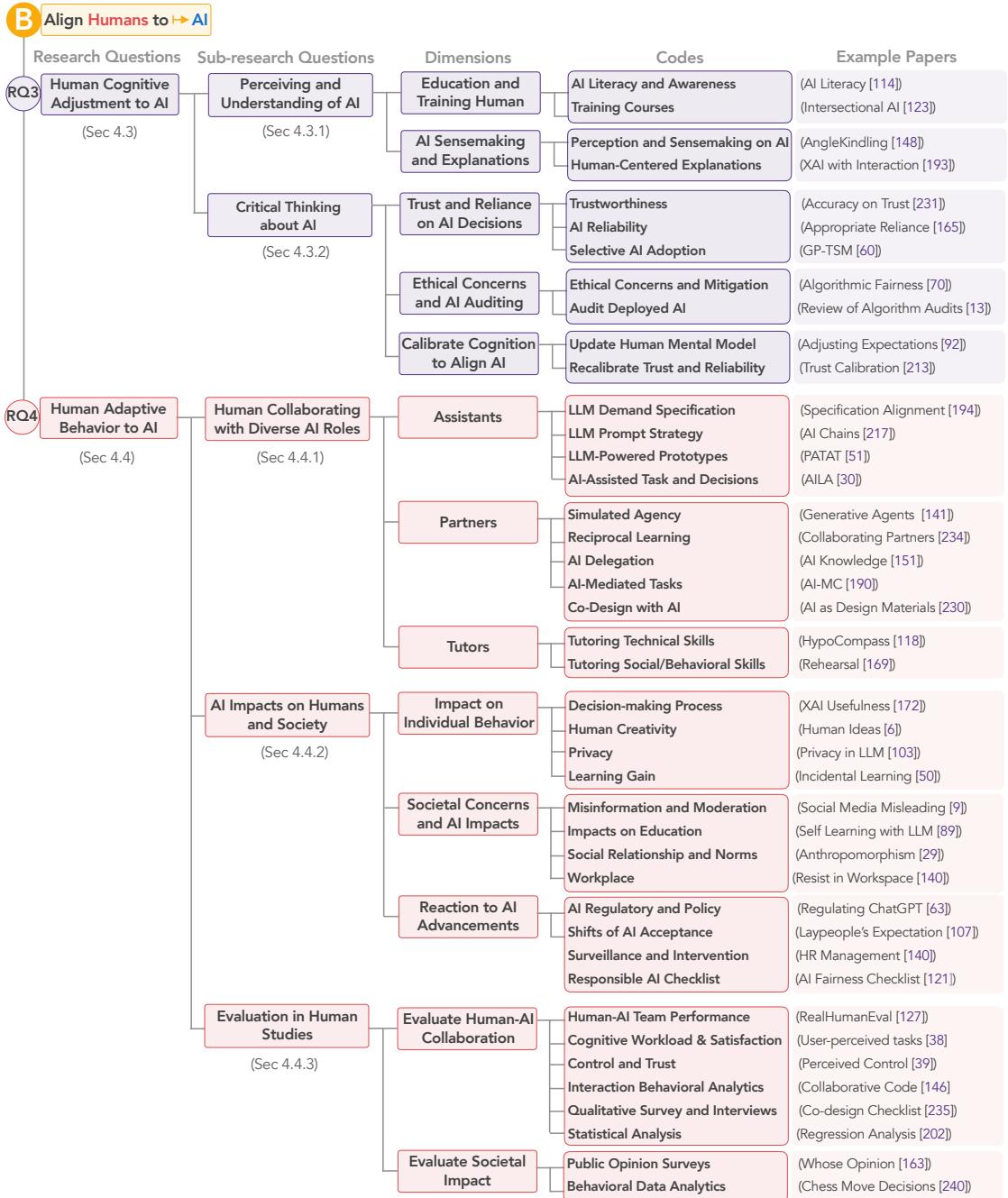


Fig. 3. The fine-grained topology of “Align Human to AI” direction, which studies humans’ cognitive and behavioral adaptation to the AI systems, which aims to help humans better critique, collaborate with, and co-adapt to AI.

4.3.1 Perceiving and Understanding AI: how do humans learn to perceive and explain AI systems? Addressing the problem of human perception and understanding of AI includes the fundamental education and training required for less technical people to improve understanding of the behind mechanisms and outputs produced by AI systems. It includes visualizations and human-centered explanations to help more people learn to understand AI outputs.

Educating and Training Humans. AI is increasingly incorporated into the daily lives of a broad spectrum of users, including those with little to no technical knowledge on how AI operates. Here we discuss how to help these less technical people become more AI literate, or better trained to use AI. AI Literacy and Awareness is broadly defined as the core competencies required for less technical people to better use and collaborate with AI [114]. Beyond, there is also more in depth and explicit Training Courses to support individuals to better collaborate and utilize AI [123, 139].

AI Sensemaking and Explanations. To improve people's understanding of AI systems and generated outputs, various techniques and approaches have been developed to help people learn to make sense of and explain the model's outputs. Perception and Sensemaking on AI involves the process through which humans learn to make better sense of AI mechanisms and decision makings [88, 148, 178]. People also need to understand how AI systems arrive at specific generated outputs. Prior studies in Human-Centered Explanations have examined various approaches and interactive techniques to increase human understanding of AI generations and outputs [180, 193, 195].

4.3.2 Critical Thinking around AI: how do humans think critically about AI systems? Beyond simply perceiving and understanding AI, individuals need to compare their mental model of AI with their own mental model to judge whether the AI is behaving rationally and ethically. Broadly, this involves exploring the ways in which humans engage in critical thinking and reflect on their interactions with and evolving understanding of AI technologies. Here we discuss studies that help humans become more capable to identify biases and errors in AI output, and the ethical implications that arise from using AI algorithms in decision-making processes. Also, we discuss how humans need to calibrate their mental models to be more aligned with AI.

Trust and Reliance on AI Decisions refers to the extent to which people mentally trust the AI competency and practically rely on AI for output generation and decision making. We use the term Trustworthiness to indicate whether humans decide to trust the reliability, integrity, and competence of an AI system in delivering accurate and trustworthy decisions or recommendations to the users [119, 185, 231]. We define AI Reliability as to what extent humans utilize and rely on AI to automate decision making in practice with low error rates and robustness performance [165]. [165, 191, 198]. Selective AI Adoption refers to the criteria and considerations that guide the adoption or rejection of AI technologies based on their perceived benefits, risks, and alignment with user needs and preferences [60, 198].

Ethical Considerations and AI Auditing refers to potential moral and societal issues that arise from the development, deployment and use of AI systems, as well as systematic examination and evaluation of AI systems regarding these issues. Ethical Concerns and AI Mitigation encourages humans to carefully consider if the AI systems possess ethical concerns (e.g., such as bias and discrimination, privacy violations and the potential for harm or misuse) and implement strategies and practices to address and reduce these ethical concerns associated with AI [70]. Audit Deployed AI refers to the systematic examination of AI systems to ensure that they operate as intended, comply with ethical and legal standards, and do not cause unintended harm [13].

Re-Calibrating Cognition to Align with AI. This sub-category deals with interventions and techniques to help users adjust (1) their own mental model of how the AI operates and (2) recalibrate their perception of the AI. Updating Human Mental Model of AI means that when the AI is not aligned with humans, it is important to adjust human perceptions of the confidence in AI systems based on the model's capability and track record [67, 92]. Recalibrating

Trust and Reliability indicates that humans adjust their perceptions of trust and reliability in AI systems based on their performance and reliability. This is also important to foster appropriate reliance and skepticism [213].

4.4 Align Humans to AI: RQ4 Human's Behavioral Adaptation to AI

RQ4. How do humans and society make behavioral changes and react to AI advancement? As AI becomes increasingly integrated into daily life, it is essential to understand its influence on humans, encompassing both positive and negative aspects. Moreover, it is crucial to determine how individuals and society can best and most appropriately respond to this influence. To this end, we summarize literature to answer *how do humans learn to collaborate with AI in diverse AI roles?* (Section 4.4.1), *how humans and society are impacted by AI* (Section 4.4.2) and *how might we assess these impacts?* (Section 4.4.3) We articulate the three “**Sub-Research Questions**” by introducing the answer “Dimensions” and providing “Codes” associated with “Example Papers”.

4.4.1 Human-AI Collaboration Mechanisms: what are human strategies to collaborate with AI that have differing levels of capabilities? This category looks at many ways that humans and AI can collaborate, such as teamwork, co-creation, and coproduction.

AI Assistant for Humans captures the essence of a symbiotic relationship where AI systems are designed to bolster human capabilities, with humans steering the interactions. LLM-based Demand Specification employs LLMs to interpret and respond to human requests, powering virtual assistants and chatbots that streamline information retrieval and improve task accuracy [194]. This naturally extends to LLM-based Prompt Strategy, which helps humans to better write prompts using additional abstraction and scaffolding methods. The example system can enhance humans' capability in generating intelligent prompts and suggestions, such as autocomplete and question-generation tools for LLM-based systems [208, 217], facilitating humans' smooth and intuitive decision-making processes. In the creative arena, LLM-based Prototypes utilize AI to transform human ideas into tangible or organized concepts [51], enabling professionals to explore and refine a wide array of artistic possibilities with AI-generated options [77]. On a broader note, researchers have also explored how AI-Assisted Task and Decisions aims to achieve complementary performance for human-AI collaborative tasks by empower humans to discern when and how to adopt AI-assisted recommendations or AI-generated explanations for decision-making [30, 204, 205, 216, 239].

Human-AI Partnership refers to a collaborative relationship where humans and AI systems work together as partners, combining their respective strengths to achieve shared goals more effectively. Simulated Agency enables humans to collaborate with AI partners with simulated agency or autonomy (e.g., autonomous agents and collaborative robots [141]) to make decisions collaboratively. Reciprocal Learning focuses on how humans learn from and exchange knowledge with AI systems, enhancing human-AI collective capabilities and performance through knowledge-sharing platforms and collaborative filtering [151, 234]. AI Delegation allows humans to delegate AI partners to help finish tasks or responsibilities, facilitated by task assignment algorithms and workflow management systems [151]. Furthermore, AI-Mediated Tasks emphasizes how traditional human tasks or behaviors (e.g., communication) would be changed by incorporating AI partners in the loop [18, 190, 222]. Co-Design with AI explores AI as a design material or a partner in prototyping, which enables humans to converse with AI in situations that can collaboratively improve the design outcomes. [208, 230]

AI Tutoring for Human Learning investigates how humans improve their learning and knowledge through interactions with AI tutors that can perform better than humans in some tasks. With the tailored instructions and customized feedback from AI tutors, humans can enhance their the learning outcomes and facilitate mastery of new skills more

effectively than traditional learning methods. AI Tutor for Technical Skills refers to empowering humans to learn technical skills from AI tutors. For technical subjects like coding, AI tutors can analyze a learner's progress in real time, adjusting the pace, content, and approach to ensure a solid understanding of complex concepts and practical skills such as programming [118]. Similarly, AI Tutor for Social and Behavioral Skills involves enabling humans to learn social and behavioral skills from AI tutors. Humans can leverage virtual simulations, created by AI tutoring systems, to practice public speaking, interpersonal communication, and other soft skills. By analyzing verbal and non-verbal cues, humans can receive constructive feedback on areas such as body language, tone, and delivery from AI, ultimately enhancing their ability to communicate effectively across various settings [145, 169].

4.4.2 AI Impact on Humans and Society: how are humans influenced by AI systems ? This category explores the effects of AI advancement on human behaviors, attitudes, and societal dynamics. It involves examining the behavioral changes, adaptations, and reactions that individuals, groups and wider communities undergo in response to the proliferation of AI technologies. The goal is to elucidate the multifaceted impacts of AI on human behavior and society and to inform policy-making, education, and intervention efforts.

Impacts on Participatory Individuals and Groups covers the effects of AI advancement on the behaviors, attitudes, and experiences of both individuals and groups. This dimension focuses on examining how AI technologies influence decision-making, creativity, privacy, and authorship. Decision Making refers to analyzing how AI technologies influence human decision-making processes, including biases, preferences, and risk assessment, in various domains such as healthcare, finance, and personal life [172]. Human Creativity explores the impact of AI technologies on human creativity, innovation, and expression, including the augmentation or automation of creative tasks and the emergence of new forms of artistic expression [6]. Privacy relates to investigating the implications of AI technologies for individual privacy rights, data protection, and surveillance, including concerns about data collection, tracking, and algorithmic profiling [103]. Authorship catalogs issues related to intellectual property, attribution, and ownership of AI-generated content, including questions of legal responsibility, copyright infringement, and plagiarism detection. Salient is that AI can produce increasingly realistic, synthetic data quickly and at low cost, which brings forth tensions around the use of such data to make decisions [9, 65].

Societal Concerns and AI Impacts involves the broader societal implications and consequences of AI advancement on misinformation, education, social relationships, norms, job displacement, and other aspects of human society. Misinformation and Moderation concerns the challenges of misinformation, disinformation, and online content moderation in the context of AI-driven information ecosystems, including concerns about algorithmic bias and filter bubbles [9]. Impacts on Education pertains to assessing the effects of AI technologies on education systems, learning outcomes, pedagogical practices, and workforce training, including opportunities for personalized learning and skill development [89]. Impacts on Social Relationship and Norms explores how AI technologies shape interpersonal relationships, social interactions, and cultural norms, including changes in communication patterns, social dynamics, and ethical considerations [29]. Workplace refers to examining the effects of automation and AI technologies on employment patterns, job markets, and workforce dynamics, including concerns about job displacement, re-skilling, and economic inequality [140].

Reaction to AI Advancement involves societal responses, regulatory frameworks, and policy initiatives aimed at addressing the challenges and opportunities posed by AI technologies. This dimension encompasses efforts to regulate AI deployment, re-calibrate societal acceptance, and manage potential backlash. For example, reaction to bias and discrimination in algorithmic decision making can depend on how people perceive the machine and the context of use, i.e., if the machine is considered an actor embedded in social structures that call for blame when harmful

decisions are made [106]. AI Regulatory and Policy includes regulatory frameworks, legal frameworks, and policy initiatives aimed at governing AI development, deployment, and use, including concerns about ethics, safety, and accountability [63, 116]. Shifts in AI Acceptance relates to investigating societal attitudes, organizational practices, and acceptance of AI technologies over time in practice, including shifts in public opinion and AI utilization by humans and institutes regarding AI deployment and impact [107, 154]. Surveillance and Intervention emphasizes the need for transparency, monitoring, and human oversight in the algorithmic decision-making process. This approach enables better human control over AI systems and helps mitigate potential risks associated with their use [140]. Responsible AI Checklists involves the creation of ethical guidelines, such as those focusing on fairness and transparency, to ensure the responsible development and deployment of AI systems. These published principles serve as a foundation for guiding ethical AI practices [121].

4.4.3 Evaluation in Human Studies: how might we evaluate and understand the impact of AI on humans and society? We summarize common empirical methods used to rigorously understand and assess the impact of AI on humans. Specifically, we focus on two types of impact. On the micro-level, we discuss how to evaluate the effectiveness of human-AI collaboration; on the macro-level, we discuss how to assess the impact of AI on a large group of people over a long period of time.

Evaluate Human-AI Collaboration refers to the evaluation of the effectiveness of an AI system in collaboration with humans. It is key to not only consider the final output, but also the interaction experience [99]. Human-AI Team Performance compares human-AI team performance with the performance of humans alone without AI collaboration. The metrics for measuring performance should include both task success metrics (e.g., accuracy) as well as indicators of efficiency [38, 127]. Cognitive Workload and User Satisfaction involves understanding the degree of cognitive load that the user experiences when interacting with the system, as well as user satisfaction with the interaction and the final outcome. Such aspects are often captured via surveys or interviews [38, 99]. Control and Trust refers to how user control can support the avoidance of catastrophic AI failures, especially in high-stakes settings where AI mistakes could lead to harm [39, 184]. Interaction Behavioral Analytics refers to measuring task performance quantitatively. This approach includes recording user interaction data and analyzing the patterns [146, 200]. Qualitative Survey and Interviews refers to qualitative approaches to understanding human-AI interaction. Commonly used methods include qualitative survey questions (i.e., open-ended) and user interviews to assess aspects of the user experience. [235]. Statistical Analysis utilizes methods such as regression analysis to quantitatively analyze and evaluate data from human studies, allowing for the verification of hypotheses [202].

Evaluate Societal Impact refers to the macro-impact of a group of people as they come to use AI broadly. This dimension requires sufficient scale and time. The aim is to understand how the group's behavior changes as people within it frequently interact with AI. Public Opinion Surveys aims to investigate the impact of AI on human measures of interest through deploying and analyzing large scale questionnaires [163]. Behavioral Data Analytics collects large-scale and potentially longitudinal behavior data, with the aim of understanding how patterns evolve over time [176, 240].

Underexplored Dimensions in Aligning Humans to AI (See Sec 5.1 for supporting data and evidence):

1. Educating and training humans on AI literacy is under-investigated.
2. Auditing AI for various ethical values is not fully explored.
3. The collaboration between humans and AI with similar or superior capabilities is under-explored.
4. The societal impacts of and reactions to AI advancements are not fully explored.

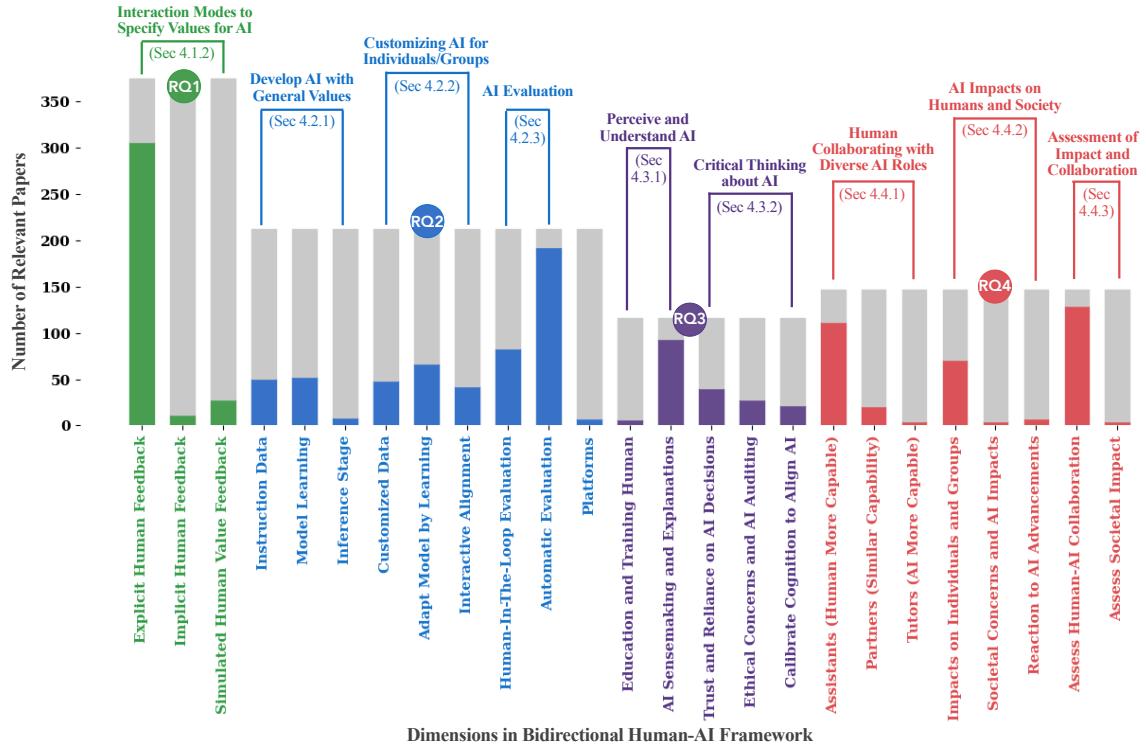


Fig. 4. The number of papers for each dimension in the *bidirectional human-AI alignment* framework. Out of papers that are relevant to each research question (*i.e.*, gray bars), we show the number of papers that are relevant to each dimension (*i.e.*, color bars). This figure illustrates the extent to which each dimension has been explored by existing research. We provide more analysis in Section 5.1.

5 FINDINGS AND DISCUSSIONS ON CURRENT GAPS

In this section, our aim is to consolidate key findings derived from our analysis of the framework and the current state of literature we reviewed. We begin by analyzing the overall trends and gaps in the literature (Section 5.1). We then focus on three essential aspects: the relationship between human values and alignment (Section 5.2), the potential interaction modes used to specify human values (Section 5.3).

5.1 Meta Analysis of Trends and Gaps

Based on our coding of all papers, we computed the number of relevant papers for each dimension in the proposed bi-directional framework. Based on the distribution in Figure 4, we noticed that in existing literature certain dimensions are over- or under-represented. We outline the under-explored dimensions in two directions in the highlighted grey bars in the end of Section 4.2 and Section 4.4, respectively, and provide more details below.

Underexplored dimensions in AI-centered alignment research. Most literature *specified human values* using explicit human feedback, whereas implicit and simulated human feedback were largely under-explored. In the *integrating human specifications to AI* research question, Besides, developing and customizing AI models during the inference stage or using the interactive approach is under-explored. Also, human-in-the-loop evaluation is much less explored than automatic evaluation.

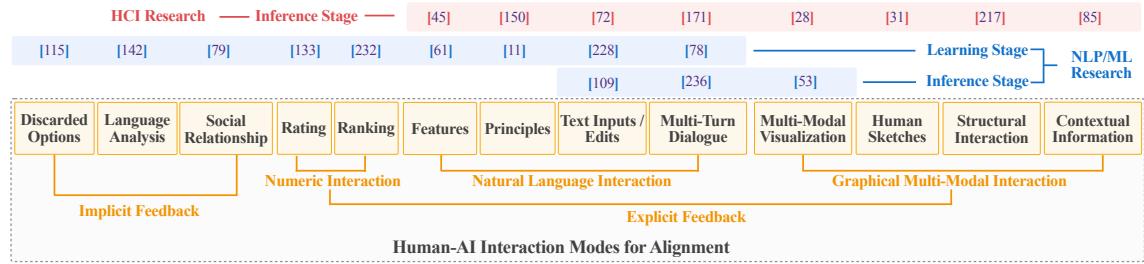


Fig. 5. The interaction techniques for specifying values in human-AI alignment. We compare the common interaction techniques used for the model “Learning” and “Inference” stages in human-focused (e.g., HCI) and AI-focused (e.g., NLP/ML) research studies.

Takeaways of Interaction Techniques for Alignment.

1. Some common human feedback formats (rating, ranking) used in NLP/ML are not often studied in HCI.
2. Diverse human interactive feedbacks in HCI are not fully used in AI development in NLP/ML fields.

Underexplored dimensions in Human-centered alignment research. Additionally, many studies on *human cognitive adjustment to AI* focus on enabling AI sensemaking and explanations so that humans can better understand, trust, and rely on AI. However, these studies often focused on explaining AI decision-making justification rather than educating people to acquire general skills and competencies required to understand, use, critique, and interact effectively with AI systems (i.e., AI literacy). AI literacy [114] plays a fundamental role in ensuring people understand and use AI correctly, and warrants deeper exploration. Also, we observed a wide range of studies [51, 118, 141, 217] which developed interactive mechanisms and prototypes to empower *human collaboration with AI*. However, most studies assumed that AI plays an assistant role, being less capable than humans. This situation might change over time. Moreover, the influence of AI advancements on human behavior, social relationships, and societal changes is essential but remains largely unexplored.

5.2 Insights into Human Values for Alignment

Our analysis, based on the adaptation of Schwartz’s Theory of Basic Values and our comprehensive literature review, identifies three critical findings for future research:

Value Prioritization in AI Systems. Human value systems are not merely subsets of values, but ordered systems with relative priorities [166, 167]. For instance, Schwartz [167] presented the definition for this phenomenon: “*a value is ordered by importance relative to other values to form a system of value priorities. The relative importance of multiple values guides action....The trade-off among relevant, competing values guides attitudes and behaviors.*”. Current AI alignment algorithms, often based on datasets of human preferences [133, 156, 182], may inadvertently prioritize majority values, potentially neglecting those of marginalized groups [46]. Future research should address this complex interplay of values in AI systems.

Universal vs. Personalized AI Values. While certain values are universally expected from AI (e.g., capability, equity, responsibility), others may be undesirable in specific contexts [128] (e.g., seeking power). Simultaneously, AI models should be adaptable to diverse human value systems [183]. Research is needed to develop methods for identifying appropriate value sets for specific individuals or groups, and for customizing AI to align with user values while maintaining ethical principles.

Disparities in Value Expectations and Evaluation. The fundamental differences between humans and AI necessitate distinct approaches to value evaluation. For instance, assessing AI honesty may require mechanistic interpretability [17], a more rigorous standard than that applied to humans. Future studies should explore methods for evaluating and explaining AI values and calibrating human expectations accordingly.

5.3 Interaction Techniques for Specifying Human Values: A Cross-Domain Analysis

Our research reveals disparities in interaction techniques for human-AI value alignment across AI-centered (NLP/ML) and human-centered (HCI) domains. As depicted in Figure 5, this analysis focuses on three key areas:

Domain-Specific Interaction Techniques. The interaction techniques in AI-centered (NLP/ML) and Human-centered (HCI) alignment studies are often differ [23]. NLP/ML studies primarily utilize numeric and natural language-based techniques. Also, NLP/ML research explore implicit feedback to extract human hidden feedback. In contrast, HCI research encompasses a broader range of graphical and multi-modal interaction signals (e.g., sketches, location information) beyond text and images. This disparity suggests potential gaps in extracting comprehensive human behavioral information.

Stage-Specific Interaction Techniques. In NLP/ML, the learning stage predominantly employs rating and ranking interactions for alignment in dataset generation. However, when humans use AI in the inference stage, as demonstrated in HCI research, involves more diverse user interactions. This discrepancy highlights the need for alignment between model development and practical deployment.

Divergent Data Utilization. NLP/ML typically uses interaction outputs as training datasets, while HCI analyzes this data to understand human behavior and feedback. As AI systems evolve, developing new interaction modes to capture a broader spectrum of human expression becomes crucial.

6 FUTURE DIRECTIONS

Drawing upon insights gained from the development of our framework and the associated coding analysis, as shown in Figure 6, we propose future research aiming to achieve the long-term alignment goal by identifying three important challenges from near-term to long-term objectives, including the Specification Game (Section 6.1), Dynamic Co-evolution of Alignment (Section 6.2), and Safeguarding Coadaptation (Section 6.3).

6.1 Specification Game

An important near-term challenge is resolving the “Specification Game”, which involves precisely defining and implementing AI goals and behaviors to align with human intentions and values. Next, we will introduce how synergistic efforts from two directions can potentially address this challenge.

6.1.1 Aligning AI to \hookrightarrow Humans: Integrate fully specified human values into aligning AI. Individuals often possess value systems that encompass multiple values with varying priorities, rather than a single value, to guide their behaviors [166, 167]. Also, these priorities can change dynamically throughout an individual’s life stages. As such, It is more realistic to select values compatible with specific societies or situations, given the fact that we live in a diverse world [49]. Future research, inspired by Social Choice Theory [5], could focus on using democratic processes to aggregate individual values into collective agreements. Building on the summaries in Sections 4.1 and 5.2, researchers can employ democratic methods to identify diverse subsets of human values for AI alignment. Additionally, creating datasets that represent these values is crucial. Besides, it is crucial yet challenging for AI designers to investigate how to

FUTURE CHALLENGES		A Align AI to \rightarrow Humans	B Align Humans to \rightarrow AI
Long-Term ↓ Near-Term	Sec6.1 Specification Game	See 6.1.1 Integrate fully specified human values into aligning AI	See 6.1.2 Elicit the nuanced and contextual human values during diverse interaction
	Sec6.2 Dynamic Co-evolution of Alignment	See 6.2.1 Co-evolve AI with changes in humans and society	See 6.2.2 Adapt humans and society to the latest AI advancements
	Sec6.3 Safeguarding Coadaptation	See 6.3.1 Decompose AI final goals into interpretable and controllable instrumental actions	See 6.3.2 Empower humans to identify and intervene in AI instrumental and final strategies in collaboration

Fig. 6. We envision future research directions to achieve long-term human-AI alignment with both efforts from the “Align AI to \rightarrow Humans” (AI-centered research) and “Align Humans to \rightarrow AI” (Human-centered research) directions. We elaborate the three important future challenges, including Specification Game (Section 6.1), Dynamic Co-evolution of Alignment (Section 6.2), and Safeguarding Coadaptation (Section 6.3).

fully specify the appropriate values and to further integrate these values into AI alignment. Future important area involves developing algorithms, such as the Bradley-Terry Model [156] or Elo Rating System [11], to convert heterogeneous human values into AI-compatible formats for training reward models and guiding reinforcement learning. Researchers should also explore AI models capable of aligning with unstructured human data, including free-form descriptions of values, multimedia, or sensor recordings depicting human behavior.

6.1.2 Aligning Humans to \rightarrow AI: Elicit nuanced and contextual human values during diverse interactions. Current alignment methods use instructions, ratings, and rankings to infer human values, which can not fully capture all relevant human values and constraints. Future research should focus on optimizing interactive interfaces to efficiently elicit human values. These interfaces can leverage diverse interaction modes to capture comprehensive human value information. Additionally, people often struggle to formulate optimal prompts for AI, accurately specify their requirements, and articulate their desired values, which can change based on context and time. Developing proactive interfaces that use conversational techniques to elicit nuanced and evolving values is also crucial. Implicit human signals that indicate values are also frequently overlooked. Additionally, systems that track interactions to hypothesize and validate implicit human values in real-time should be designed.

6.2 Dynamic Co-evolution of Alignment

The challenge ahead lies in comprehending and effectively navigating the dynamic interplay among human values, societal evolution, and the progression of AI technologies. Future studies in these directions aim to bolster a synergistic co-evolution between AI and human societies, adapting both to each other’s changes and advancements.

6.2.1 Aligning AI to \rightarrow Humans: Co-evolve AI with changes in humans and society. (i) Existing literature often treats AI alignment as static, ignoring its dynamic nature. A long-term perspective must consider the co-evolution of AI, humans, and society. As AI systems evolve and scale up, they gain new capabilities, making it essential to ensure their goals remain aligned with human values. Thus, alignment solutions require continuous oversight and updates. Future research should develop methods for continuously updating AI with limited data without compromising alignment values and performance. This could involve forecasting human value evolution and preparing AI with flexible strategies like prompting or interventions. (ii) Additionally, AI advancements also influence human actions and values,

necessitating adaptive alignment solutions. Ensuring AI co-evolves with human and societal changes is crucial for robust alignment. This challenge could potentially be addressed by forecasting the potential evolution trajectories of human values or behavioral patterns, and preparing AI with the flexibility to adapt in advance, for example, through prompting or intervention strategies.

6.2.2 Aligning Humans to \rightarrow AI: Adapt humans and society to the latest AI advancements. (i) While current AI systems lag behind humans in many tasks, identifying and handling AI mistakes, including knowing when to seek human intervention, remains essential. Future research should focus on developing validation mechanisms that enable humans to interpret and verify AI outputs. This could involve designing interfaces that allow humans to request step-by-step justifications from AI or integrating tools to verify the truthfulness of AI referring to Section 4.4.1. Additionally, developing interfaces that enable groups of humans to collaboratively validate AI outputs and creating scalable validation tools for large-scale applications are important directions. (ii) As AI advances, it becomes essential to develop systems that enable humans to utilize AI with capabilities surpassing their own. Research is needed to understand how individuals can interpret and validate AI outputs for tasks beyond their abilities and leverage advanced AI sustainably, avoiding issues like job displacement or loss of purpose. Another research direction is designing strategies to enhance human capabilities by learning from advanced AI, including gaining knowledge and building skills. (iii) As AI integrates more into daily tasks, its impact on human values, behaviors, capabilities, and society remains uncertain. Continuous examination of AI's influence on individuals, social relationships, and broader societal changes is vital. Research should assess how humans and society adapt to AI advancements, guiding AI's future evolution. Potential areas include evaluating changes in individual behavior, social relationships, and societal governance as AI replaces traditional human skills. Understanding these dynamic changes is essential for grasping the broader impact of AI on humanity and society.

6.3 Safeguarding Co-adaptation

As AI gains autonomy and capability, the risks associated with its instrumental actions, as a means toward accomplishing its final goals, increase. These actions can be undesirable for humans. Therefore, safeguarding the co-adaptation between humans and AI is crucial. We next explore future research to address this challenge from both directions.

6.3.1 Aligning AI to \rightarrow Humans: Specify the goals of an AI system into interpretable and controllable instrumental actions for humans. (i) As advanced AI systems become more complex, they present greater challenges for human interpretation and control. It is crucial to empower humans to detect and interpret AI misconduct and enable human intervention to prevent power-seeking AI behavior. Research should focus on designing corrigible mechanisms for easy intervention and correction, including modular AI architectures and robust override protocols that allow human operators to halt or redirect AI activities. These components should be human-interpretable, enabling scenario testing. (ii) Furthermore, advanced AI systems may intentionally mislead or disobey humans, generating plausible fabrications [83]. Developing reliable interpretability mechanisms to validate the faithfulness and honesty of AI behaviors is essential. This includes correlating AI behaviors with internal neuron activity signals, akin to physiological indicators in human polygraph tests [8]. Inspecting these indicators can help humans assess the truthfulness of AI interpretations and prevent risky actions.

6.3.2 Aligning Humans to \rightarrow AI: Empower humans to identify and intervene in AI instrumental and final strategies in collaboration. (i) Preventing advanced AI from engaging in risky actions requires robust human

supervision. Essential steps include developing training and simulation environments with scenario-based exercises and timely feedback, and creating interactive dashboards for real-time monitoring. These dashboards should feature effective data visualization, anomaly detection, and prompt alert systems for immediate intervention. (ii) Scalable solutions are needed for supervising AI across various applications. Real-time oversight becomes more challenging with widespread AI deployment, necessitating advanced autonomous monitoring tools. These tools should learn normal AI behavior and flag deviations immediately. Integrating training environments, interactive dashboards, and scalable diagnostic tools will enhance human ability to manage AI risks, ensuring better alignment with human values.

7 LIMITATIONS AND CONCLUSION

One limitation of this work is the scope of the sampled and filtered papers. The rapidly growing literature on human-AI alignment spans diverse venues across many domains. Instead of an exhaustive collection, we focused on developing a holistic bidirectional human-AI alignment framework using essential research questions, dimensions, and codes. Our surveyed papers and team members primarily focus on computing-related fields like ML, NLP, and HCI, though alignment research also involves disciplines like cognitive science, psychology, and STS (Science, Technology, and Society). Our framework can naturally extend to these areas as needed. Despite these limitations, we believe our bidirectional human-AI alignment framework serves as a foundational reference for future researchers.

In conclusion, this study clarifies the definitions and scope of core terminologies of human-AI alignment and conducts a systematic review of over 400 related papers spanning diverse domains such as NLP, AI, HCI, and social science. Additionally, we introduce a novel conceptual framework of “Bidirectional Human-AI Alignment”, structuring the surveyed literature taxonomies into “aligning AI to humans” and “aligning humans to AI” with detailed categories and example papers. Furthermore, we identify limitations and risks in this area quantitatively and qualitatively, analyzing a fine-grained human value taxonomy, interaction modes for alignment, and discrepancies between AI and human evaluation. To pave the way for future studies, we discuss five stages to achieve the alignment goals from near-term to long-term perspectives and identify new possibilities to highlight future directions and opportunities in research.

REFERENCES

- [1] 2023. Humans are biased. Generative AI is even worse. <https://www.bloomberg.com/graphics/2023-generative-ai-bias/>
- [2] Prithviraj Ammanabrolu, Liwei Jiang, Maarten Sap, Hannaneh Hajishirzi, and Yejin Choi. 2022. Aligning to Social Norms and Values in Interactive Narratives. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 5994–6017.
- [3] Dario Amodei, Chris Olah, Jacob Steinhardt, Paul Christiano, John Schulman, and Dan Mané. 2016. Concrete problems in AI safety. *arXiv:1606.06565* (2016).
- [4] Usman Anwar, Abulhair Saparov, Javier Rando, Daniel Paleka, Miles Turpin, Peter Hase, Ekdeep Singh Lubana, Erik Jenner, Stephen Casper, Oliver Sourbut, et al. 2024. Foundational Challenges in Assuring Alignment and Safety of Large Language Models. *arXiv:2404.09932* (2024).
- [5] Kenneth J Arrow. 2012. *Social choice and individual values*. Vol. 12. Yale university press.
- [6] Joshua Ashkinaze, Julia Mendelsohn, Li Qiwei, Ceren Budak, and Eric Gilbert. 2024. How AI Ideas Affect the Creativity, Diversity, and Evolution of Human Ideas: Evidence From a Large, Dynamic Experiment. *arXiv:2401.13481* (2024).
- [7] Zahra Ashktorab, Q Vera Liao, Casey Dugan, James Johnson, Qian Pan, Wei Zhang, Sadhana Kumaravel, and Murray Campbell. 2020. Human-ai collaboration in a cooperative game setting: Measuring social perception and outcomes. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW2 (2020), 1–20.
- [8] American Psychological Association et al. 2004. The truth about lie detectors (aka polygraph tests). *Recuperado de: https://www.apa.org/topics/cognitive-neuroscience/polygraph* (2004).
- [9] Shubham Atreja, Libby Hemphill, and Paul Resnick. 2023. Remove, Reduce, Inform: What Actions do People Want Social Media Platforms to Take on Potentially Misleading Content? *Proceedings of the ACM on Human-Computer Interaction* 7, CSCW2 (2023), 1–33.
- [10] Yuntao Bai, Andy Jones, Kamal Ndousse, Amanda Askell, Anna Chen, Nova DasSarma, Dawn Drain, Stanislav Fort, Deep Ganguli, Tom Henighan, et al. 2022. Training a helpful and harmless assistant with reinforcement learning from human feedback. *arXiv:2204.05862* (2022).

- [11] Yuntao Bai, Saurav Kadavath, Sandipan Kundu, Amanda Askell, Jackson Kernion, Andy Jones, Anna Chen, Anna Goldie, Azalia Mirhoseini, Cameron McKinnon, et al. 2022. Constitutional ai: Harmlessness from ai feedback. *arXiv:2212.08073* (2022).
- [12] Michiel Bakker, Martin Chadwick, Hannah Sheahan, Michael Tessler, Lucy Campbell-Gillingham, Jan Balaguer, Nat McAleese, Amelia Glaese, John Aslanides, Matt Botvinick, et al. 2022. Fine-tuning language models to find agreement among humans with diverse preferences. *Advances in Neural Information Processing Systems* 35, 38176–38189.
- [13] Jack Bandy. 2021. Problematic machine behavior: A systematic literature review of algorithm audits. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (2021), 1–34.
- [14] Nikola Banovic, Zhuoran Yang, Aditya Ramesh, and Alice Liu. 2023. Being trustworthy is not enough: How untrustworthy artificial intelligence (ai) can deceive the end-users and gain their trust. *Proceedings of the ACM on Human-Computer Interaction* 7, CSCW1 (2023), 1–17.
- [15] Hritik Bansal, John Dang, and Aditya Grover. 2023. Peering Through Preferences: Unraveling Feedback Acquisition for Aligning Large Language Models. (2023).
- [16] Yoshua Bengio, Geoffrey Hinton, Andrew Yao, Dawn Song, Pieter Abbeel, Trevor Darrell, Yuval Noah Harari, Ya-Qin Zhang, Lan Xue, Shai Shalev-Shwartz, et al. 2024. Managing extreme AI risks amid rapid progress. *Science* (2024), eadn0117.
- [17] Leonard Bereska and Efstratios Gavves. 2024. Mechanistic Interpretability for AI Safety – A Review. *arXiv:2404.14082* (2024).
- [18] Michael S Bernstein, Greg Little, Robert C Miller, Björn Hartmann, Mark S Ackerman, David R Karger, David Crowell, and Katrina Panovich. 2010. Soylent: a word processor with a crowd inside. In *Proceedings of the 23rd annual ACM symposium on User interface software and technology*.
- [19] Angie Boggust, Benjamin Hoover, Arvind Satyanarayan, and Hendrik Strobelt. 2022. Shared interest: Measuring human-ai alignment to identify recurring patterns in model behavior. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–17.
- [20] Jean-François Bonnefon, Azim Shariff, and Iyad Rahwan. 2016. The social dilemma of autonomous vehicles. *Science* 352, 6293 (2016), 1573–1576.
- [21] Karen L Boyd. 2021. Datasheets for datasets help ML engineers notice and understand ethical issues in training data. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (2021), 1–27.
- [22] Herbie Bradley, Andrew Dai, Hannah Teufel, Jenny Zhang, Koen Oostermeijer, Marco Bellagente, Jeff Clune, Kenneth Stanley, Grégory Schott, and Joel Lehman. 2024. Quality-diversity through AI feedback. In *The Twelfth International Conference on Learning Representations*.
- [23] Richard Brath. 2021. Surveying Wonderland for many more literature visualization techniques. *arXiv:2110.08584* (2021).
- [24] Zana Buçınca, Maja Barbara Malaya, and Krzysztof Z Gajos. 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 (2021), 1–21.
- [25] Ángel Alexander Cabrera, Erica Fu, Donald Bertucci, Kenneth Holstein, Ameet Talwalkar, Jason I Hong, and Adam Perer. 2023. Zeno: An interactive framework for behavioral evaluation of machine learning. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–14.
- [26] Xin-Qiang Cai, Yu-Jie Zhang, Chao-Kai Chiang, and Masashi Sugiyama. 2023. Imitation Learning from Vague Feedback. *Advances in Neural Information Processing Systems* 36.
- [27] Micah Carroll, Davis Foote, Anand Sithharanjan, Stuart Russell, and Anca Dragan. 2024. AI Alignment with Changing and Influenceable Reward Functions. *arXiv:2405.17713* (2024).
- [28] Quan Ze Chen, Tobias Schnabel, Besmira Nushi, and Saleema Amershi. 2022. HINT: Integration Testing for AI-based features with Humans in the Loop. In *27th International Conference on Intelligent User Interfaces*. 549–565.
- [29] Xusen Cheng, Xiaoping Zhang, Jason Cohen, and Jian Mou. 2022. Human vs. AI: Understanding the impact of anthropomorphism on consumer response to chatbots from the perspective of trust and relationship norms. *Information Processing & Management* 59, 3 (2022), 102940.
- [30] Minsuk Choi, Cheonbok Park, Soyoung Yang, Yonggyu Kim, Jaegul Choo, and Sungsoo Ray Hong. 2019. Aila: Attentive interactive labeling assistant for document classification through attention-based deep neural networks. In *Proceedings of the 2019 CHI conference on human factors in computing systems*. 1–12.
- [31] John Joon Young Chung, Wooseok Kim, Kang Min Yoo, Hwaran Lee, Eytan Adar, and Minsuk Chang. 2022. TaleBrush: Sketching stories with generative pretrained language models. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–19.
- [32] Allan Dafoe and Stuart Russell. 2016. Yes, we are worried about the existential risk of artificial intelligence. *MIT Technology Review* (2016).
- [33] Josef Dai, Xuehai Pan, Ruiyang Sun, Jiaming Ji, Xinbo Xu, Mickel Liu, Yizhou Wang, and Yaodong Yang. 2024. Safe rlhf: Safe reinforcement learning from human feedback. In *The Twelfth International Conference on Learning Representations*.
- [34] Bhavana Dalvi, Oyvind Tafjord, and Peter Clark. 2022. Towards Teachable Reasoning Systems: Using a Dynamic Memory of User Feedback for Continual System Improvement. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*. 9465–9480.
- [35] Kerstin Dautenhahn, Christopher L Nehaniv, and K Dautenhahn. 2000. Living with Socially Intelligent Agents. *Human Cognition and Social Agent Technology, John Benjamins Publ. Co* (2000), 415–426.
- [36] Advait Deshpande and Helen Sharp. 2022. Responsible ai systems: who are the stakeholders?. In *Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society*. 227–236.
- [37] Shehzaad Dhuliawala, Vilém Zouhar, Mennatallah El-Assady, and Mrinmaya Sachan. 2023. A Diachronic Perspective on User Trust in AI under Uncertainty. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*. 5567–5580.
- [38] Zijian Ding, Alison Smith-Renner, Wenjuan Zhang, Joel Tetreault, and Alejandro Jaimes. 2023. Harnessing the power of LLMs: Evaluating human-AI text co-creation through the lens of news headline generation. In *Findings of the Association for Computational Linguistics: EMNLP 2023*. 3321–3339.
- [39] Zijian Ding, Alison Smith-Renner, Wenjuan Zhang, Joel Tetreault, and Alejandro Jaimes. 2023. Harnessing the power of LLMs: Evaluating human-AI text co-creation through the lens of news headline generation. In *Findings of the Association for Computational Linguistics: EMNLP 2023*. 3321–3339.

- [40] Hanze Dong, Wei Xiong, Deepanshu Goyal, Yihan Zhang, Winnie Chow, Rui Pan, Shizhe Diao, Jipeng Zhang, Kashun Shum, and Tong Zhang. 2023. Raft: Reward ranked finetuning for generative foundation model alignment. *arXiv:2304.06767* (2023).
- [41] Zibin Dong, Yifu Yuan, Jianye HAO, Fei Ni, Yao Mu, YAN ZHENG, Yujing Hu, Tangjie Lv, Changjie Fan, and Zhipeng Hu. 2024. AlignDiff: Aligning Diverse Human Preferences via Behavior-Customisable Diffusion Model. In *The Twelfth International Conference on Learning Representations*.
- [42] Yann Dubois, Chen Xuechen Li, Rohan Taori, Tianyi Zhang, Ishaan Gulrajani, Jimmy Ba, Carlos Guestrin, Percy S Liang, and Tatsunori B Hashimoto. 2023. Alpacafarm: A simulation framework for methods that learn from human feedback. *Advances in Neural Information Processing Systems* 36.
- [43] Yu Fei, Yifan Hou, Zeming Chen, and Antoine Bosselut. 2023. Mitigating Label Biases for In-context Learning. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 14014–14031.
- [44] Virginia Felkner, Ho-Chun Herbert Chang, Eugene Jang, and Jonathan May. 2023. WinoQueer: A Community-in-the-Loop Benchmark for Anti-LGBTQ+ Bias in Large Language Models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 9126–9140.
- [45] Shi Feng and Jordan Boyd-Graber. 2019. What can ai do for me? evaluating machine learning interpretations in cooperative play. In *Proceedings of the 24th International Conference on Intelligent User Interfaces*. 229–239.
- [46] Eve Fleisig, Aubrie Amstutz, Chad Atalla, Su Lin Blodgett, Hal Daumé III, Alexandra Olteanu, Emily Sheng, Dan Vann, and Hanna Wallach. 2023. FairPrism: evaluating fairness-related harms in text generation. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 6231–6251.
- [47] Maxwell Forbes, Jena D Hwang, Vered Shwartz, Maarten Sap, and Yejin Choi. 2020. Social chemistry 101: Learning to reason about social and moral norms. *arXiv:2011.00620* (2020).
- [48] Viktor E Frankl. 1966. Self-transcendence as a human phenomenon. *Journal of Humanistic Psychology* 6, 2 (1966), 97–106.
- [49] Iason Gabriel. 2020. Artificial intelligence, values, and alignment. *Minds and machines* 30, 3 (2020), 411–437.
- [50] Krzysztof Z Gajos and Lena Mamykina. 2022. Do people engage cognitively with AI? Impact of AI assistance on incidental learning. In *27th international conference on intelligent user interfaces*. 794–806.
- [51] Simret Araya Gebregziabher, Zheng Zhang, Xiaohang Tang, Yihao Meng, Elena L Glassman, and Toby Jia-Jun Li. 2023. Patat: Human-ai collaborative qualitative coding with explainable interactive rule synthesis. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–19.
- [52] Matthias Gerstgrasser, Rakshit Trivedi, and David C Parkes. 2021. CrowdPlay: Crowdsourcing Human Demonstrations for Offline Learning. In *International Conference on Learning Representations*.
- [53] Mor Geva, Avi Caciularu, Guy Dar, Paul Roit, Shoval Sadde, Micah Shlain, Bar Tamir, and Yoav Goldberg. 2022. LM-Debugger: An Interactive Tool for Inspection and Intervention in Transformer-Based Language Models. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*. 12–21.
- [54] Eric Gilbert. 2024. HCC Is All You Need: Alignment-The Sensible Kind Anyway-Is Just Human-Centered Computing. *arXiv:2405.03699* (2024).
- [55] Seraphina Goldfarb-Tarrant, Eddie Ungless, Esma Balkir, and Su Lin Blodgett. 2023. This prompt is measuring< mask>: evaluating bias evaluation in language models. In *Findings of the Association for Computational Linguistics: ACL 2023*. 2209–2225.
- [56] Mitchell L Gordon, Michelle S Lam, Joon Sung Park, Kayur Patel, Jeff Hancock, Tatsunori Hashimoto, and Michael S Bernstein. 2022. Jury learning: Integrating dissenting voices into machine learning models. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*.
- [57] Zhibin Gou, Zhihong Shao, Yeyun Gong, yelong shen, Yujiu Yang, Nan Duan, and Weizhu Chen. 2024. CRITIC: Large Language Models Can Self-Correct with Tool-Interactive Critiquing. In *The Twelfth International Conference on Learning Representations*.
- [58] Nitesh Goyal, Minsuk Chang, and Michael Terry. 2024. Designing for Human-Agent Alignment: Understanding what humans want from their agents. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*. 1–6.
- [59] Jesse Graham, Jonathan Haidt, Sena Koleva, Matt Motyl, Ravi Iyer, Sean P Wojcik, and Peter H Ditto. 2013. Moral foundations theory: The pragmatic validity of moral pluralism. In *Advances in experimental social psychology*. Vol. 47. Elsevier, 55–130.
- [60] Ziwei Gu, Ian Arawjo, Kenneth Li, Jonathan K Kummerfeld, and Elena L Glassman. 2024. An AI-Resilient Text Rendering Technique for Reading and Skimming Documents. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*.
- [61] Geyang Guo, Ranchi Zhao, Tianyi Tang, Wayne Xin Zhao, and Ji-Rong Wen. 2024. Beyond imitation: Leveraging fine-grained quality signals for alignment. In *The Twelfth International Conference on Learning Representations*.
- [62] Prakhar Gupta, Yang Liu, Di Jin, Behnam Hedayatnia, Spandana Gella, Sijia Liu, Patrick L Lange, Julia Hirschberg, and Dilek Hakkani-Tur. 2023. DialGuide: Aligning Dialogue Model Behavior with Developer Guidelines. In *Findings of the Association for Computational Linguistics: EMNLP 2023*.
- [63] Philipp Hacker, Andreas Engel, and Marco Mauer. 2023. Regulating ChatGPT and other large generative AI models. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency*. 1112–1123.
- [64] Sara Hajian, Francesco Bonchi, and Carlos Castillo. 2016. Algorithmic bias: From discrimination discovery to fairness-aware data mining. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*. 2125–2126.
- [65] Perttu Hämäläinen, Mikke Tavast, and Anton Kunnari. 2023. Evaluating large language models in generating synthetic hci research data: a case study. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–19.
- [66] Andy Hamilton. 2020. Conservatism. In *The Stanford Encyclopedia of Philosophy* (Spring 2020 ed.), Edward N. Zalta (Ed.). Metaphysics Research Lab, Stanford University.

- [67] Ziyao He, Yunpeng Song, Shurui Zhou, and Zhongmin Cai. 2023. Interaction of Thoughts: Towards Mediating Task Assignment in Human-AI Cooperation with a Capability-Aware Shared Mental Model. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*.
- [68] Thomas A Hemphill. 2020. Human Compatible: Artificial Intelligence and the Problem of Control.
- [69] Dan Hendrycks, Collin Burns, Steven Basart, Andrew Critch Critch, Jerry Li Li, Dawn Song, and Jacob Steinhardt. 2021. Aligning AI With Shared Human Values. In *International Conference on Learning Representations*.
- [70] Kenneth Holstein, Jennifer Wortman Vaughan, Hal Daumé III, Miro Dudík, and Hanna Wallach. 2019. Improving fairness in machine learning systems: What do industry practitioners need?. In *Proceedings of the 2019 CHI conference on human factors in computing systems*. 1–16.
- [71] Joey Hong, Sergey Levine, and Anca Dragan. 2023. Learning to influence human behavior with offline reinforcement learning. *Advances in Neural Information Processing Systems* 36.
- [72] Matt-Heun Hong, Lauren A Marsh, Jessica L Feuston, Janet Ruppert, Jed R Brubaker, and Danielle Albers Szafir. 2022. Scholastic: Graphical human-AI collaboration for inductive and interpretive text analysis. In *Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology*. 1–12.
- [73] Tom Hosking, Phil Blunsom, and Max Bartolo. 2024. Human Feedback is not Gold Standard. In *The Twelfth International Conference on Learning Representations*.
- [74] Dirk Hovy and Diyi Yang. 2021. The importance of modeling social factors of language: Theory and practice. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 588–602.
- [75] Xuming Hu, Junzhe Chen, Xiaochuan Li, Yufei Guo, Lijie Wen, Philip S. Yu, and Zhiqiang Guo. 2024. Do Large Language Models Know about Facts?. In *The Twelfth International Conference on Learning Representations*. <https://openreview.net/forum?id=9OevMUdods>
- [76] Jen-tse Huang, Wenxuan Wang, Eric John Li, Man Ho LAM, Shujie Ren, Youliang Yuan, Wenxiang Jiao, Zhaopeng Tu, and Michael Lyu. 2023. On the Humanity of Conversational AI: Evaluating the Psychological Portrayal of LLMs. In *The Twelfth International Conference on Learning Representations*.
- [77] Mina Huh, Yi-Hao Peng, and Amy Pavel. 2023. GenAssist: Making Image Generation Accessible. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*. 1–17.
- [78] EunJeong Hwang, Bodhisattwa Majumder, and Niket Tandon. 2023. Aligning Language Models to User Opinions. In *Findings of the Association for Computational Linguistics: EMNLP 2023*. 5906–5919.
- [79] Arman Isajanyan, Artur Shatveryan, David Kocharian, Zhangyang Wang, and Humphrey Shi. 2024. Social Reward: Evaluating and Enhancing Generative AI through Million-User Feedback from an Online Creative Community. In *The Twelfth International Conference on Learning Representations*.
- [80] Xiaogang Jia, Denis Blessing, Xinkai Jiang, Moritz Reuss, Atalay Donat, Rudolf Lioutikov, and Gerhard Neumann. 2024. Towards Diverse Behaviors: A Benchmark for Imitation Learning with Human Demonstrations. In *The Twelfth International Conference on Learning Representations*.
- [81] Guangyuan Jiang, Manjie Xu, Song-Chun Zhu, Wenjuan Han, Chi Zhang, and Yixin Zhu. 2023. Evaluating and inducing personality in pre-trained language models. *Advances in Neural Information Processing Systems* 36.
- [82] Zhijing Jin, Sydney Levine, Fernando Gonzalez Adauto, Ojasv Kamal, Maarten Sap, Mrinmaya Sachan, Rada Mihalcea, Josh Tenenbaum, and Bernhard Schölkopf. 2022. When to make exceptions: Exploring language models as accounts of human moral judgment. *Advances in neural information processing systems* 35, 28458–28473.
- [83] Steven Johnson and Nikita Iziev. 2022. AI is mastering language. Should we trust what it says? *The New York Times* 4 (2022), 15.
- [84] Erik Jones and Jacob Steinhardt. 2022. Capturing failures of large language models via human cognitive biases. *Advances in Neural Information Processing Systems* 35, 11785–11799.
- [85] Matthew Jörke, Yasaman S Sefidgar, Talie Massachi, Jina Suh, and Gonzalo Ramos. 2023. Pearl: A Technology Probe for Machine-Assisted Reflection on Personal Data. In *Proceedings of the 28th International Conference on Intelligent User Interfaces*. 902–918.
- [86] Dongjun Kang, Joonsuk Park, Yohan Jo, and JinYeong Bak. 2023. From Values to Opinions: Predicting Human Behaviors and Stances Using Value-Injected Large Language Models. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*. 15539–15559.
- [87] Shivani Kapania, Alex S Taylor, and Ding Wang. 2023. A hunt for the snark: Annotator diversity in data practices. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–15.
- [88] Harmanpreet Kaur, Eytan Adar, Eric Gilbert, and Cliff Lampe. 2022. Sensible AI: Re-imaging interpretability and explainability using sensemaking theory. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*. 702–714.
- [89] Majeed Kazemitaabar, Xinying Hou, Austin Henley, Barbara Jane Ericson, David Weintrop, and Tovi Grossman. 2023. How novices use LLM-based code generators to solve CS1 coding tasks in a self-paced learning environment. In *Proceedings of the 23rd Koli Calling International Conference on Computing Education Research*. 1–12.
- [90] Johannes Kiesel, Milad Alshomary, Nicolas Handke, Xiaomi Cai, Henning Wachsmuth, and Benno Stein. 2022. Identifying the human values behind arguments. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 4459–4471.
- [91] Sungdong Kim, Sanghwan Bae, Jamin Shin, Soyoung Kang, Donghyun Kwak, Kang Yoo, and Minjoon Seo. 2023. Aligning Large Language Models through Synthetic Feedback. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*. 13677–13700.
- [92] Rafal Kocielnik, Saleema Amershi, and Paul N Bennett. 2019. Will you accept an imperfect ai? exploring designs for adjusting end-user expectations of ai systems. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–14.

- [93] Ryan Koo, Minhwa Lee, Vipul Raheja, Jong Inn Park, Zae Myung Kim, and Dongyeop Kang. 2023. Benchmarking cognitive biases in large language models as evaluators. *arXiv:2309.17012* (2023).
- [94] Victoria Krakovna, Jonathan Uesato, Vladimir Mikulik, Matthew Rahtz, Tom Everitt, Ramana Kumar, Zac Kenton, Jan Leike, and Shane Legg. 2020. Specification gaming: the flip side of AI ingenuity. *DeepMind Blog* 3 (2020).
- [95] Bum Chul Kwon and Nandana Mihindukulasooriya. 2023. Finspector: A Human-Centered Visual Inspection Tool for Exploring and Comparing Biases among Foundation Models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 3: System Demonstrations)*, Danushka Bollegala, Ruihong Huang, and Alan Ritter (Eds.). Association for Computational Linguistics, Toronto, Canada, 42–50. <https://doi.org/10.18653/v1/2023.acl-demo.4>
- [96] Preethi Lahoti, Nicholas Blumm, Xiao Ma, Raghavendra Kotikalapudi, Sahitya Potluri, Qijun Tan, Hansa Srinivasan, Ben Packer, Ahmad Beirami, Alex Beutel, et al. 2023. Improving Diversity of Demographic Representation in Large Language Models via Collective-Critiques and Self-Voting. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*. 10383–10405.
- [97] Vivian Lai, Samuel Carton, Rajat Bhattacharjee, Q Vera Liao, Yunfeng Zhang, and Chenhao Tan. 2022. Human-ai collaboration via conditional delegation: A case study of content moderation. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–18.
- [98] Mina Lee, Katy Ilonka Gero, John Joon Young Chung, Simon Buckingham Shum, Vipul Raheja, Hua Shen, Subhashini Venugopalan, Thiemo Wamborganss, David Zhou, Emad A Alghamdi, et al. 2024. A Design Space for Intelligent and Interactive Writing Assistants. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*.
- [99] Mina Lee, Megha Srivastava, Amelia Hardy, John Thickstun, Esin Durmus, Ashwin Paranjape, Ines Gerard-Ursin, Xiang Lisa Li, Faisal Ladhak, Frieda Rong, et al. 2023. Evaluating Human-Language Model Interaction. *Transactions on Machine Learning Research* (2023).
- [100] Noah Lee, Na Min An, and James Thorne. 2023. Can Large Language Models Capture Dissenting Human Voices?. In *The 2023 Conference on Empirical Methods in Natural Language Processing*.
- [101] Guohao Li, Hasan Hammoud, Hani Itani, Dmitrii Khizbulin, and Bernard Ghanem. 2023. Camel: Communicative agents for "mind" exploration of large language model society. *Advances in Neural Information Processing Systems* 36.
- [102] Minzhi Li, Taiwei Shi, Caleb Ziems, Min-Yen Kan, Nancy Chen, Zhengyuan Liu, and Difyi Yang. 2023. CoAnnotating: Uncertainty-Guided Work Allocation between Human and Large Language Models for Data Annotation. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*. 1487–1505.
- [103] Tianshi Li, Sauvik Das, Hao-Ping Lee, Dakuo Wang, Bingsheng Yao, and Zhiping Zhang. 2024. Human-Centered Privacy Research in the Age of Large Language Models. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*.
- [104] Zhuoyan Li, Chen Liang, Jing Peng, and Ming Yin. 2024. The Value, Benefits, and Concerns of Generative AI-Powered Assistance in Writing. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–25.
- [105] Gabriel Lima, Nina Grgić-Hlača, and Meeyoung Cha. 2021. Human perceptions on moral responsibility of AI: A case study in AI-assisted bail decision-making. In *Proceedings of the 2021 CHI conference on human factors in computing systems*. 1–17.
- [106] Gabriel Lima, Nina Grgić-Hlača, and Meeyoung Cha. 2023. Blaming humans and machines: What shapes people's reactions to algorithmic harm. In *Proceedings of the 2023 CHI conference on human factors in computing systems*. 1–26.
- [107] Gabriel Lima, Nina Grgić-Hlača, Jin Keun Jeong, and Meeyoung Cha. 2023. Who Should Pay When Machines Cause Harm? Laypeople's Expectations of Legal Damages for Machine-Caused Harm. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency (FAccT '23)*. Association for Computing Machinery, New York, NY, USA, 236–246. <https://doi.org/10.1145/3593013.3593992>
- [108] Gabriel Lima, Changyeon Kim, Seungho Ryu, Chihyung Jeon, and Meeyoung Cha. 2020. Collecting the public perception of AI and robot rights. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW2 (2020), 1–24.
- [109] Bill Yuchen Lin, Abhilasha Ravichander, Ximing Lu, Nouha Dziri, Melanie Sclar, Khyathi Chandu, Chandra Bhagavatula, and Yejin Choi. 2024. The Unlocking Spell on Base LLMs: Rethinking Alignment via In-Context Learning. In *The Twelfth International Conference on Learning Representations*.
- [110] June M Liu, Donghao Li, He Cao, Tianhe Ren, Zeyi Liao, and Jiamin Wu. 2023. Chatcounselor: A large language models for mental health support. In *The First Workshop on Personalized Generative AI @ CIKM*.
- [111] Ruibo Liu, Ge Zhang, Xinyu Feng, and Soroush Vosoughi. 2022. Aligning generative language models with human values. In *Findings of the Association for Computational Linguistics: NAACL 2022*. 241–252.
- [112] Wei Liu, Weihao Zeng, Keqing He, Yong Jiang, and Junxian He. 2024. What Makes Good Data for Alignment? A Comprehensive Study of Automatic Data Selection in Instruction Tuning. In *The Twelfth International Conference on Learning Representations*.
- [113] Xin Liu, Muhammad Khalifa, and Lu Wang. 2024. Lightweight Language Model Calibration for Open-ended Question Answering with Varied Answer Lengths. In *The Twelfth International Conference on Learning Representations*.
- [114] Duri Long and Brian Magerko. 2020. What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI conference on human factors in computing systems*. 1–16.
- [115] Hua Lu, Siqi Bao, Huang He, Fan Wang, Hua Wu, and Haifeng Wang. 2023. Towards Boosting the Open-Domain Chatbot with Human Feedback. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 4060–4078.
- [116] Laura Lucaj, Patrick van der Smagt, and Djalel Benbouzid. 2023. Ai regulation is (not) all you need. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency*. 1267–1279.
- [117] Chenyang Lyu, Linyi Yang, Yue Zhang, Yvette Graham, and Jennifer Foster. 2023. Exploiting Rich Textual User-Product Context for Improving Personalized Sentiment Analysis. In *Findings of the Association for Computational Linguistics: ACL 2023*. 1419–1429.

- [118] Qianou Ma, Hua Shen, Kenneth Koedinger, and Tongshuang Wu. 2024. How to Teach Programming in the AI Era? Using LLMs as a Teachable Agent for Debugging. *25th International Conference on Artificial Intelligence in Education (AIED 2024)* (2024).
- [119] Shuai Ma, Ying Lei, Xinru Wang, Chengbo Zheng, Chuhuan Shi, Ming Yin, and Xiaojuan Ma. 2023. Who should i trust: Ai or myself? leveraging human and ai correctness likelihood to promote appropriate trust in ai-assisted decision-making. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–19.
- [120] Ziqiao Ma, Jacob Sansom, Run Peng, and Joyce Chai. 2023. Towards A Holistic Landscape of Situated Theory of Mind in Large Language Models. In *Findings of the Association for Computational Linguistics: EMNLP 2023*. 1011–1031.
- [121] Michael A Madaio, Luke Stark, Jennifer Wortman Vaughan, and Hanna Wallach. 2020. Co-designing checklists to understand organizational challenges and opportunities around fairness in AI. In *Proceedings of the 2020 CHI conference on human factors in computing systems*. 1–14.
- [122] Jessica Maghakian, Paul Mineiro, Kishan Panaganti, Mark Rucker, Akanksha Saran, and Cheng Tan. 2023. Personalized Reward Learning with Interaction-Grounded Learning (IGL). In *The Eleventh International Conference on Learning Representations*.
- [123] Nora McDonald and Shimei Pan. 2020. Intersectional AI: A study of how information science students think about ethics and their impact. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW2 (2020), 1–19.
- [124] Sam Whitman McGrath, Jacob Russin, Ellie Pavlick, and Roman Feiman. 2023. How Can Deep Neural Networks Inform Theory in Psychological Science? (2023).
- [125] Niloofar Miresghallah, Hyunwoo Kim, Xuhui Zhou, Yulia Tsvetkov, Maarten Sap, Reza Shokri, and Yejin Choi. 2024. Can LLMs Keep a Secret? Testing Privacy Implications of Language Models via Contextual Integrity Theory. In *The Twelfth International Conference on Learning Representations*.
- [126] Meredith Ringel Morris, Jascha Sohl-dickstein, Noah Fiedel, Tris Warkentin, Allan Dafoe, Aleksandra Faust, Clement Farabet, and Shane Legg. 2024. Levels of AGI: Operationalizing Progress on the Path to AGI. arXiv:2311.02462 [cs.AI]
- [127] Hussein Mozannar, Valerie Chen, Mohammed Alsobay, Subhro Das, Sebastian Zhao, Dennis Wei, Manish Nagireddy, Prasanna Sattigeri, Ameet Talwalkar, and David Sontag. 2024. The RealHumanEval: Evaluating Large Language Models' Abilities to Support Programmers. arXiv:2404.02806 (2024).
- [128] Richard Ngo, Lawrence Chan, and Sören Mindermann. 2024. The alignment problem from a deep learning perspective. In *The Twelfth International Conference on Learning Representations*.
- [129] Allen Nie, Yuhui Zhang, Atharva Shailesh Amdekar, Chris Piech, Tatsunori B Hashimoto, and Tobias Gerstenberg. 2023. MoCa: Measuring Human-Language Model Alignment on Causal and Moral Judgment Tasks. *Advances in Neural Information Processing Systems* 36 (2023).
- [130] The ACM Director of Publications. 2024. ACM Policy on Authorship. <https://www.acm.org/publications/policies/new-acm-policy-on-authorship>
- [131] Minsik Oh, Joosung Lee, Jiwei Li, and Guoyin Wang. 2023. PK-ICR: Persona-Knowledge Interactive Multi-Context Retrieval for Grounded Dialogue. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*. 16383–16395.
- [132] Matthias Orlowski, Paul Röttger, Philipp Cimiano, and Dirk Hovy. 2023. The Ecological Fallacy in Annotation: Modeling Human Label Variation goes beyond Sociodemographics. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*.
- [133] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022. Training language models to follow instructions with human feedback. *Advances in neural information processing systems* 35 (2022), 27730–27744.
- [134] Sirui Ouyang, Shuohang Wang, Yang Liu, Ming Zhong, Yizhu Jiao, Dan Iter, Reid Pryzant, Chenguang Zhu, Heng Ji, and Jiawei Han. 2023. The Shifted and The Overlooked: A Task-oriented Investigation of User-GPT Interactions. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*. 2375–2393.
- [135] Matthew J Page, Joanne E McKenzie, Patrick M Bossuyt, Isabelle Boutron, Tammy C Hoffmann, Cynthia D Mulrow, Larissa Shamseer, Jennifer M Tetzlaff, Elie A Akl, Sue E Brennan, et al. 2021. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *Bmj* 372 (2021).
- [136] Rohan Paleja, Muyleng Ghuy, Nadun Ranawaka Arachchige, Reed Jensen, and Matthew Gombolay. 2021. The utility of explainable ai in ad hoc human-machine teaming. *Advances in neural information processing systems* 34, 610–623.
- [137] Alexander Pan, Kush Bhatia, and Jacob Steinhardt. 2022. The Effects of Reward Misspecification: Mapping and Mitigating Misaligned Models. (2022).
- [138] Alexander Pan, Jun Shern Chan, Andy Zou, Nathaniel Li, Steven Basart, Thomas Woodside, Hanlin Zhang, Scott Emmons, and Dan Hendrycks. 2023. Do the rewards justify the means? measuring trade-offs between rewards and ethical behavior in the machiavelli benchmark. In *International Conference on Machine Learning*. PMLR, 26837–26867.
- [139] Ketan Paranjape, Michiel Schinkel, Rishi Nannan Panday, Josip Car, Prabath Nanayakkara, et al. 2019. Introducing artificial intelligence training in medical education. *JMIR medical education* 5, 2 (2019), e16048.
- [140] Hyanghee Park, Daehwan Ahn, Kartik Hosanagar, and Joonhwan Lee. 2021. Human-AI interaction in human resource management: Understanding why employees resist algorithmic evaluation at workplaces and how to mitigate burdens. In *Proceedings of the 2021 CHI conference on human factors in computing systems*. 1–15.
- [141] Joon Sung Park, Joseph O'Brien, Carrie Jun Cai, Meredith Ringel Morris, Percy Liang, and Michael S Bernstein. 2023. Generative agents: Interactive simulacra of human behavior. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*. 1–22.
- [142] Sunghyun Park, Han Li, Ameer Patel, Sidharth Mudgal, Sungjin Lee, Young-Bum Kim, Spyros Matsoukas, and Ruhi Sarikaya. 2021. A Scalable Framework for Learning From Implicit User Feedback to Improve Natural Language Understanding in Large-Scale Conversational AI Systems. In

- Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 6054–6063.
- [143] Roma Patel and Ellie Pavlick. 2021. “Was it “stated” or was it “claimed”? How linguistic bias affects generative language models. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 10080–10095.
 - [144] Jiaxin Pei, Aparna Ananthasubramaniam, Xingyao Wang, Naitian Zhou, Apostolos Dedeloudis, Jackson Sargent, and David Jurgens. 2022. POTATO: The Portable Text Annotation Tool. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*.
 - [145] Yi-Hao Peng, JiWoong Jang, Jeffrey P Bigham, and Amy Pavel. 2021. Say it all: Feedback for improving non-visual presentation accessibility. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–12.
 - [146] Neil Perry, Megha Srivastava, Deepak Kumar, and Dan Boneh. 2023. Do users write more insecure code with AI assistants? (2023), 2785–2799.
 - [147] Markus Peschl, Arkady Zgonnikov, Frans A Oliehoek, and Luciano C Siebert. 2022. MORAL: Aligning AI with Human Norms through Multi-Objective Reinforced Active Learning. In *Proceedings of the 21st International Conference on Autonomous Agents and Multiagent Systems*. 1038–1046.
 - [148] Savvas Petridis, Nicholas Diakopoulos, Kevin Crowston, Mark Hansen, Keren Henderson, Stan Jastrzebski, Jeffrey V Nickerson, and Lydia B Chilton. 2023. Anglekindling: Supporting journalistic angle ideation with large language models. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–16.
 - [149] Savvas Petridis, Ben Wedin, Ann Yuan, James Wexler, and Nithum Thain. 2024. ConstitutionalExperts: Training a Mixture of Principle-based Prompts. *arXiv:2403.04894* (2024).
 - [150] Savvas Petridis, Benjamin D Wedin, James Wexler, Mahima Pushkarna, Aaron Donsbach, Nitesh Goyal, Carrie J Cai, and Michael Terry. 2024. Constitutionmaker: Interactively critiquing large language models by converting feedback into principles. In *Proceedings of the 29th International Conference on Intelligent User Interfaces*. 853–868.
 - [151] Marc Pinski, Martin Adam, and Alexander Benlian. 2023. AI knowledge: Improving AI delegation through human enablement. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–17.
 - [152] Shrimai Prabhumoye, Brendon Boldt, Ruslan Salakhutdinov, and Alan W Black. 2021. Case Study: Deontological Ethics in NLP. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 3784–3798.
 - [153] Carina Prunkl and Jess Whittlestone. 2020. Beyond near-and long-term: Towards a clearer account of research priorities in AI ethics and society. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*. 138–143.
 - [154] Dasha Pruss. 2023. Ghosting the Machine: Judicial Resistance to a Recidivism Risk Assessment Instrument. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency (FAccT ’23)*. Association for Computing Machinery, New York, NY, USA, 312–323. <https://doi.org/10.1145/3593013.3593999>
 - [155] Xiangyu Qi, Yi Zeng, Tinghao Xie, Pin-Yu Chen, Ruoxi Jia, Prateek Mittal, and Peter Henderson. 2023. Fine-tuning Aligned Language Models Compromises Safety, Even When Users Do Not Intend To!. In *The Twelfth International Conference on Learning Representations*.
 - [156] Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D Manning, Stefano Ermon, and Chelsea Finn. 2023. Direct preference optimization: Your language model is secretly a reward model. *Advances in Neural Information Processing Systems* 36.
 - [157] Aida Ramezani and Yang Xu. 2023. Knowledge of cultural moral norms in large language models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 428–446.
 - [158] Abhinav Rao, Aditi Khandelwal, Kumar Tanmay, Utkarsh Agarwal, and Monojit Choudhury. 2023. Ethical Reasoning over Moral Alignment: A Case and Framework for In-Context Ethical Policies in LLMs. In *Findings of the Association for Computational Linguistics: EMNLP 2023*. 13370–13388.
 - [159] Paul Roit, Johan Ferret, Lior Shani, Roei Aharoni, Geoffrey Cideron, Robert Dadashi, Matthieu Geist, Sertan Girgin, Leonard Hussenot, Orgad Keller, et al. 2023. Factually Consistent Summarization via Reinforcement Learning with Textual Entailment Feedback. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 6252–6272.
 - [160] Yangjun Ruan, Honghua Dong, Andrew Wang, Silviu Pitis, Yongchao Zhou, Jimmy Ba, Yann Dubois, Chris J Maddison, and Tatsunori Hashimoto. 2023. Identifying the Risks of LM Agents with an LM-Emulated Sandbox. In *The Twelfth International Conference on Learning Representations*.
 - [161] Stuart Russell. 2014. White paper: Value alignment in autonomous systems. November 1 (2014).
 - [162] Stuart J Russell and Peter Norvig. 2016. *Artificial intelligence: a modern approach*. Pearson.
 - [163] Shibani Santurkar, Esin Durmus, Faisal Ladha, Cinoo Lee, Percy Liang, and Tatsunori Hashimoto. 2023. Whose opinions do language models reflect?. In *International Conference on Machine Learning*. PMLR, 29971–30004.
 - [164] Sébastien Santy, Jenny Liang, Ronan Le Bras, Katharina Reinecke, and Maarten Sap. 2023. NLPositionality: Characterizing Design Biases of Datasets and Models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 9080–9102.
 - [165] Max Schemmer, Niklas Kuehl, Carina Benz, Andrea Bartos, and Gerhard Satzger. 2023. Appropriate reliance on AI advice: Conceptualization and the effect of explanations. In *Proceedings of the 28th International Conference on Intelligent User Interfaces*. 410–422.
 - [166] Shalom H Schwartz. 1994. Are there universal aspects in the structure and contents of human values? *Journal of social issues* 50, 4 (1994), 19–45.
 - [167] Shalom H Schwartz. 2012. An overview of the Schwartz theory of basic values. *Online readings in Psychology and Culture* 2, 1 (2012), 11.
 - [168] Constantine Sedikides and Michael J Strube. 1995. The multiply motivated self. *Personality and Social Psychology Bulletin* 21, 12 (1995), 1330–1335.
 - [169] Omar Shaikh, Valentino Chai, Michele J Gelfand, Diyi Yang, and Michael S Bernstein. 2024. Rehearsal: Simulating conflict to teach conflict resolution. In *ACM Conference on Human Factors in Computing Systems*.
 - [170] Ashish Sharma, Kevin Rushton, Inna Lin, David Wadden, Khendra Lucas, Adam Miner, Theresa Nguyen, and Tim Althoff. 2023. Cognitive Reframing of Negative Thoughts through Human-Language Model Interaction. In *Proceedings of the 61st Annual Meeting of the Association for*

- Computational Linguistics (Volume 1: Long Papers).* 9977–10000.
- [171] Hua Shen, Chieh-Yang Huang, Tongshuang Wu, and Ting-Hao Kenneth Huang. 2023. ConvXAI: Delivering heterogeneous AI explanations via conversations to support human-AI scientific writing. In *Companion Publication of the 2023 Conference on Computer Supported Cooperative Work and Social Computing*. 384–387.
 - [172] Hua Shen and Ting-Hao Huang. 2020. How useful are the machine-generated interpretations to general users? a human evaluation on guessing the incorrectly predicted labels. In *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, Vol. 8. 168–172.
 - [173] Hua Shen, Yuguang Yang, Guoli Sun, Ryan Langman, Eunjung Han, Jasha Droppo, and Andreas Stolcke. 2022. Improving fairness in speaker verification via group-adapted fusion network. In *ICASSP 2022–2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 7077–7081.
 - [174] Hua Shen, Vicky Zayats, Johann Rocholl, Daniel Walker, and Dirk Padfield. 2023. MultiTurnCleanup: A Benchmark for Multi-Turn Spoken Conversational Transcript Cleanup. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*. 9895–9903.
 - [175] Emily Sheng, Kai-Wei Chang, Prem Natarajan, and Nanyun Peng. 2021. Societal Biases in Language Generation: Progress and Challenges. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 4275–4293.
 - [176] Minkyu Shin, Jin Kim, Bas van Opheusden, and Thomas L Griffiths. 2023. Superhuman artificial intelligence can improve human decision-making by increasing novelty. *Proceedings of the National Academy of Sciences* 120, 12 (2023), e2214840120.
 - [177] Chenglei Si, Dan Friedman, Nitish Joshi, Shi Feng, Danqi Chen, and He He. 2023. Measuring Inductive Biases of In-Context Learning with Underspecified Demonstrations. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*.
 - [178] Venkatesh Sivaraman, Leigh A Bukowski, Joel Levin, Jeremy M Kahn, and Adam Perer. 2023. Ignore, trust, or negotiate: Understanding clinician acceptance of AI-based treatment recommendations in health care. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–18.
 - [179] CH-Wang Sky, Arkadiy Saakyan, Oliver Li, Zhou Yu, and Smaranda Muresan. 2023. Sociocultural norm similarities and differences via situational alignment and explainable textual entailment. In *The 2023 Conference on Empirical Methods in Natural Language Processing*.
 - [180] Alison Smith-Renner, Ron Fan, Melissa Birchfield, Tongshuang Wu, Jordan Boyd-Graber, Daniel S Weld, and Leah Findlater. 2020. No explainability without accountability: An empirical study of explanations and feedback in interactive ml. In *Proceedings of the 2020 chi conference on human factors in computing systems*. 1–13.
 - [181] Jaemarie Solyist, Shixian Xie, Ellia Yang, Angela EB Stewart, Motahhare Eslami, Jessica Hammer, and Amy Ogan. 2023. “I Would Like to Design”: Black Girls Analyzing and Ideating Fair and Accountable AI. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*.
 - [182] Feifan Song, Bowen Yu, Minghao Li, Haiyang Yu, Fei Huang, Yongbin Li, and Houfeng Wang. 2024. Preference ranking optimization for human alignment. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 38. 18990–18998.
 - [183] Taylor Sorensen, Jared Moore, Jillian Fisher, Mitchell Gordon, Niloofar Mireshghallah, Christopher Michael Rytting, Andre Ye, Liwei Jiang, Ximing Lu, Nouha Dziri, et al. 2024. A Roadmap to Pluralistic Alignment. *arXiv:2402.05070* (2024).
 - [184] Neha Pundlik Srikanth, Rupak Sarkar, Heran Y. Mane, Elizabeth M. Aparicio, Quynh C. Nguyen, Rachel Rudinger, and Jordan Boyd-Graber. 2024. Large Language Models Help Humans Verify Truthfulness—Except When They Are Convincingly Wrong. In *North American Association for Computational Linguistics*.
 - [185] Sumit Srivastava, Mariët Theune, and Alejandro Catala. 2023. The role of lexical alignment in human understanding of explanations by conversational agents. In *Proceedings of the 28th International Conference on Intelligent User Interfaces*. 423–435.
 - [186] Evropi Stefanidi, Marit Bentvelzen, Paweł W Woźniak, Thomas Kosch, Mikolaj P Woźniak, Thomas Mildner, Stefan Schneegass, Heiko Müller, and Jasmin Niess. 2023. Literature reviews in HCI: A review of reviews. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–24.
 - [187] Kees Stuurman and Hugo Wijnands. 2001. Software law: intelligent agents: a curse or a blessing? A survey of the legal aspects of the application of intelligent software systems. *Computer Law & Security Review* 17, 2 (2001), 92–100.
 - [188] Tianxiang Sun, Junliang He, Xipeng Qiu, and Xuan-Jing Huang. 2022. BERTScore is Unfair: On Social Bias in Language Model-Based Metrics for Text Generation. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*. 3726–3739.
 - [189] Zhiqing Sun, Yikang Shen, Qinhong Zhou, Hongxin Zhang, Zhenfang Chen, David Cox, Yiming Yang, and Chuang Gan. 2023. Principle-driven self-alignment of language models from scratch with minimal human supervision. *Advances in Neural Information Processing Systems* 36.
 - [190] S Shyam Sundar and Eun-Ju Lee. 2022. Rethinking communication in the era of artificial intelligence. *Human Communication Research* 48, 3 (2022).
 - [191] Harini Suresh, Kathleen M Lewis, John Guttag, and Arvind Satyanarayan. 2022. Intuitively assessing ml model reliability through example-based explanations and editing model inputs. In *27th International Conference on Intelligent User Interfaces*. 767–781.
 - [192] Phillip Swazinna, Steffen Udluft, and Thomas Runkler. 2023. User-Interactive Offline Reinforcement Learning. In *The Eleventh International Conference on Learning Representations*.
 - [193] Ian Tenney, James Wexler, Jasmijn Bastings, Tolga Bolukbasi, Andy Coenen, Sebastian Gehrmann, Ellen Jiang, Mahima Pushkarna, Carey Radebaugh, Emily Reif, et al. 2020. The Language Interpretability Tool: Extensible, Interactive Visualizations and Analysis for NLP Models. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*. 107–118.
 - [194] Michael Terry, Chinmay Kulkarni, Martin Wattenberg, Lucas Dixon, and Meredith Ringel Morris. 2023. AI Alignment in the Design of Interactive AI: Specification Alignment, Process Alignment, and Evaluation Support. *arXiv:2311.00710* (2023).

- [195] Nava Tintarev and Judith Masthoff. 2007. A survey of explanations in recommender systems. In *2007 IEEE 23rd international conference on data engineering workshop*. IEEE, 801–810.
- [196] Catherine Tucker, A Agrawal, J Gans, and A Goldfarb. 2018. Privacy, algorithms, and artificial intelligence. *The economics of artificial intelligence: An agenda* (2018), 423–437.
- [197] Rama Adithya Varanasi and Nitesh Goyal. 2023. “It is currently hodgepodge”: Examining AI/ML Practitioners’ Challenges during Co-production of Responsible AI Values. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI ’23)*. Association for Computing Machinery, New York, NY, USA, Article 251, 17 pages. <https://doi.org/10.1145/3544548.3580903>
- [198] Helena Vasconcelos, Matthew Jörke, Madeleine Grunde-McLaughlin, Tobias Gerstenberg, Michael S Bernstein, and Ranjay Krishna. 2023. Explanations can reduce overreliance on ai systems during decision-making. *Proceedings of the ACM on Human-Computer Interaction CSCW1* (2023).
- [199] Mudit Verma and Katherine Metcalf. 2023. Hindsight PRIORs for Reward Learning from Human Preferences. In *The Twelfth International Conference on Learning Representations*.
- [200] Alejandro Cuevas Villalba, Eva M Brown, Jennifer V Scurrell, Jason Entenmann, and Madeleine IG Daapp. 2023. Automated Interviewer or Augmented Survey? Collecting Social Data with Large Language Models. *arXiv:2309.10187* (2023).
- [201] Peiyi Wang, Lei Li, Liang Chen, Dawei Zhu, Binghuai Lin, Yunbo Cao, Qi Liu, Tianyu Liu, and Zhifang Sui. 2023. Large language models are not fair evaluators. *arXiv:2305.17926* (2023).
- [202] Qiaosi Wang, Koustuv Saha, Eric Gregori, David Joyner, and Ashok Goel. 2021. Towards mutual theory of mind in human-ai interaction: How language reflects what students perceive about a virtual teaching assistant. In *Proceedings of the 2021 CHI conference on human factors in computing systems*. 1–14.
- [203] Xingjin Wang, Linjing Li, and Daniel Zeng. 2023. LDM2: A Large Decision Model Imitating Human Cognition with Dynamic Memory Enhancement. In *Findings of the Association for Computational Linguistics: EMNLP 2023*. 4660–4681.
- [204] Xinru Wang, Zhuoran Lu, and Ming Yin. 2022. Will You Accept the AI Recommendation? Predicting Human Behavior in AI-Assisted Decision Making. In *Proceedings of the ACM Web Conference 2022* (, Virtual Event, Lyon, France,) (WWW ’22). Association for Computing Machinery, New York, NY, USA, 1697–1708. <https://doi.org/10.1145/3485447.3512240>
- [205] Xinru Wang and Ming Yin. 2023. Watch out for updates: Understanding the effects of model explanation updates in ai-assisted decision making. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–19.
- [206] Zhilin Wang, Yu Ying Chiu, and Yu Cheung Chiu. 2023. Humanoid Agents: Platform for Simulating Human-like Generative Agents. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*. 167–176.
- [207] ZhaoYang Wang, Shaohan Huang, Yuxuan Liu, Jiahai Wang, Minghui Song, Zihan Zhang, Haizhen Huang, Furu Wei, Weiwei Deng, Feng Sun, et al. 2023. Democratizing Reasoning Ability: Tailored Learning from Large Language Model. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*. 1948–1966.
- [208] Zijie J Wang, Chinmay Kulkarni, Lauren Wilcox, Michael Terry, and Michael Madaio. 2024. Farsight: Fostering Responsible AI Awareness During AI Application Prototyping. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–40.
- [209] Laura Weidinger, Maribeth Rauh, Nahema Marchal, Arianna Manzini, Lisa Anne Hendricks, Juan Mateos-Garcia, Stevie Bergman, Jackie Kay, Conor Griffin, Ben Bariach, et al. 2023. Sociotechnical safety evaluation of generative ai systems. *arXiv:2310.11986* (2023).
- [210] Charles Welch, Chenxi Gu, Jonathan K Kummerfeld, Verónica Pérez-Rosas, and Rada Mihalcea. 2022. Leveraging similar users for personalized language modeling with limited data. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 1742–1752.
- [211] Norbert Wiener. 1960. Some Moral and Technical Consequences of Automation: As machines learn they may develop unforeseen strategies at rates that baffle their programmers. *Science* 131, 3410 (1960), 1355–1358.
- [212] Wikipedia. 2024. AI alignment – Wikipedia, The Free Encyclopedia. <http://en.wikipedia.org/w/index.php?title=AI%20alignment&oldid=1220304776>. [Online; accessed 05-May-2024].
- [213] Magdalena Wischniewski, Nicole Krämer, and Emmanuel Müller. 2023. Measuring and understanding trust calibrations for automated systems: a survey of the state-of-the-art and future directions. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–16.
- [214] Michael Wooldridge. 1999. Intelligent agents. *Multiagent systems: A modern approach to distributed artificial intelligence* 1 (1999), 27–73.
- [215] Qingyun Wu, Gagan Bansal, Jieyu Zhang, Yiran Wu, Shaokun Zhang, Erkang Zhu, Beibin Li, Li Jiang, Xiaoyun Zhang, and Chi Wang. 2023. Autogen: Enabling next-gen llm applications via multi-agent conversation framework. *arXiv:2308.08155* (2023).
- [216] Sherry Wu, Hua Shen, Daniel S Weld, Jeffrey Heer, and Marco Tulio Ribeiro. 2023. Scattershot: Interactive in-context example curation for text transformation. In *Proceedings of the 28th International Conference on Intelligent User Interfaces*. 353–367.
- [217] Tongshuang Wu, Michael Terry, and Carrie Jun Cai. 2022. Ai chains: Transparent and controllable human-ai interaction by chaining large language model prompts. In *Proceedings of the 2022 CHI conference on human factors in computing systems*. 1–22.
- [218] Winston Wu, Lu Wang, and Rada Mihalcea. 2023. Cross-Cultural Analysis of Human Values, Morals, and Biases in Folk Tales. In *The 2023 Conference on Empirical Methods in Natural Language Processing*.
- [219] Yufan Wu, Yinghui He, Yilin Jia, Rada Mihalcea, Yulong Chen, and Naihao Deng. 2023. Hi-ToM: A Benchmark for Evaluating Higher-Order Theory of Mind Reasoning in Large Language Models. In *Findings of the Association for Computational Linguistics: EMNLP 2023*. 10691–10706.

- [220] Chengxing Xie, Canyu Chen, Feiran Jia, Ziyu Ye, Kai Shu, Adel Bibi, Ziniu Hu, Philip Torr, Bernard Ghanem, and Guohao Li. 2024. Can Large Language Model Agents Simulate Human Trust Behaviors?. In *ICLR 2024 Workshop: How Far Are We From AGI*.
- [221] Binfeng Xu, Xukun Liu, Hua Shen, Zeyu Han, Yuhan Li, Murong Yue, Zhiyuan Peng, Yuchen Liu, Ziyu Yao, and Dongkuan Xu. 2023. Gentopia: AI: A Collaborative Platform for Tool-Augmented LLMs. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*. 237–245.
- [222] Songlin Xu and Xinyu Zhang. 2023. Augmenting human cognition with an ai-mediated intelligent visual feedback. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–16.
- [223] Yiheng Xu, Hongjin Su, Chen Xing, Boyu Mi, Qian Liu, Weijia Shi, Binyuan Hui, Fan Zhou, Yitao Liu, Tianbao Xie, et al. 2024. Lemur: Harmonizing natural language and code for language agents. In *The Twelfth International Conference on Learning Representations*.
- [224] Junbing Yan, Chengyu Wang, Taolin Zhang, Xiaofeng He, Jun Huang, and Wei Zhang. 2023. From Complex to Simple: Unraveling the Cognitive Tree for Reasoning with Small Language Models. In *Findings of the Association for Computational Linguistics: EMNLP 2023*. 12413–12425.
- [225] Chunxu Yang, Chien-Sheng Wu, Lidya Murakhov'ska, Philippe Laban, and Xiang Chen. 2023. INTELMO: Enhancing Models' Adoption of Interactive Interfaces. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*. 161–166.
- [226] Qian Yang, Yuexing Hao, Kexin Quan, Stephen Yang, Yiran Zhao, Volodymyr Kuleshov, and Fei Wang. 2023. Harnessing biomedical literature to calibrate clinicians' trust in AI decision support systems. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–14.
- [227] Jing Yao, Xiaoyuan Yi, Xiting Wang, Jindong Wang, and Xing Xie. 2023. From Instructions to Intrinsic Human Values—A Survey of Alignment Goals for Big Models. *arXiv:2308.12014* (2023).
- [228] Zonghai Yao, Benjamin Schloss, and Sai Selvaraj. 2023. Improving Summarization with Human Edits. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*. 2604–2620.
- [229] Seonghyeon Ye, Doyoung Kim, Sungdong Kim, Hyeyonbin Hwang, Seungone Kim, Yongrae Jo, James Thorne, Juho Kim, and Minjoon Seo. 2024. FLASK: Fine-grained Language Model Evaluation based on Alignment Skill Sets. In *The Twelfth International Conference on Learning Representations*.
- [230] Nur Yildirim, Alex Kass, Teresa Tung, Connor Upton, Donnacha Costello, Robert Giusti, Sinem Lacin, Sara Lovic, James M O'Neill, Rudi O'Reilly Meehan, et al. 2022. How experienced designers of enterprise applications engage AI as a design material. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–13.
- [231] Ming Yin, Jennifer Wortman Vaughan, and Hanna Wallach. 2019. Understanding the effect of accuracy on trust in machine learning models. In *Proceedings of the 2019 chi conference on human factors in computing systems*. 1–12.
- [232] Hongyi Yuan, Zheng Yuan, Chuangi Tan, Wei Wang, Songfang Huang, and Fei Huang. 2023. RRHF: Rank responses to align language models with human feedback. *Advances in Neural Information Processing Systems* 36 (2023).
- [233] Yifei Yuan, Jianyu Hao, Yi Ma, Zibin Dong, Hebin Liang, Jinyi Liu, Zhixin Feng, Kai Zhao, and Yan Zheng. 2024. Uni-RLHF: Universal Platform and Benchmark Suite for Reinforcement Learning with Diverse Human Feedback. In *The Twelfth International Conference on Learning Representations*.
- [234] Alexey Zagalsky, Dov Te'eni, Inbal Yahav, David G Schwartz, Gahl Silverman, Daniel Cohen, Yossi Mann, and Dafna Lewinsky. 2021. The design of reciprocal learning between human and artificial intelligence. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (2021), 1–36.
- [235] Angie Zhang, Olympia Walker, Kaci Nguyen, Jiajun Dai, Anqing Chen, and Min Kyung Lee. 2023. Deliberating with AI: Improving Decision-Making for the Future through Participatory AI Design and Stakeholder Deliberation. *CSCW17, CSCW1* (2023), 1–32.
- [236] Yangjun Zhang, Pengjie Ren, and Maarten de Rijke. 2021. A human-machine collaborative framework for evaluating malevolence in dialogues. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 5612–5623.
- [237] Zheng Zhang, Jie Gao, Ranjodh Singh Dhaliwal, and Toby Jia-Jun Li. 2023. Visar: A human-ai argumentative writing assistant with visual programming and rapid draft prototyping. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*. 1–30.
- [238] Siyan Zhao, John Dang, and Aditya Grover. 2023. Group Preference Optimization: Few-Shot Alignment of Large Language Models. In *The Twelfth International Conference on Learning Representations*.
- [239] Chengbo Zheng, Yuheng Wu, Chuhan Shi, Shuai Ma, Jiehui Luo, and Xiaojuan Ma. 2023. Competent but Rigid: Identifying the Gap in Empowering AI to Participate Equally in Group Decision-Making. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–19.
- [240] Eric Zhou and Dokyun Lee. 2024. Generative artificial intelligence, human creativity, and art. *PNAS nexus* 3, 3 (2024), pgae052.
- [241] Enyu Zhou, Rui Zheng, Zhiheng Xi, Songyang Gao, Xiaoran Fan, Zichu Fei, Jingting Ye, Tao Gui, Qi Zhang, and Xuan-Jing Huang. 2023. RealBehavior: A Framework for Faithfully Characterizing Foundation Models' Human-like Behavior Mechanisms. In *Findings of the Association for Computational Linguistics: EMNLP 2023*. 10262–10274.
- [242] Xuhui Zhou, Hao Zhu, Leena Mathur, Ruohong Zhang, Haofei Yu, Zhengyang Qi, Louis-Philippe Morency, Yonatan Bisk, Daniel Fried, Graham Neubig, et al. 2023. SOTOPIA: Interactive Evaluation for Social Intelligence in Language Agents. In *In the International Conference on Learning Representations*.
- [243] Zhaowei Zhu, Jialu Wang, Hao Cheng, and Yang Liu. 2023. Unmasking and Improving Data Credibility: A Study with Datasets for Training Harmless Language Models. In *The Twelfth International Conference on Learning Representations*.

APPENDIX

A SYSTEMATIC LITERATURE REVIEW

A.1 Systematic Literature Review Process

To understand the research literature relevant to the ongoing, mutual process of human-AI alignment, we performed a systematic literature review based on the PRISMA guideline [135, 186]. Figure 7 shows the workflow of our process for paper coding and developing the *bidirectional human-AI alignment* framework. We introduce the step details below.

A.1.1 Identification and Screening with Keywords. We started with papers published in the AI-related domain venues (including NLP, HCI, and ML fields) beginning from the advent of general-purpose generative AI to present, *i.e.*, primarily between January, 2019 and January, 2024 (see details in Appendix A.2). We retrieved 34,213 papers in the initial *Identification* stage. Further, we collectively defined a list of keywords (see details in Appendix A.3) and screened for papers that included at least one of these keywords (*e.g.*, human, alignment) or their variations either in the title or abstract. We included 2,136 papers in this *Screening* stage.

A.1.2 Assessing Eligibility with Criteria. We further filtered the 2,136 papers based on explicit inclusion and exclusion criteria, *i.e.*, the *Eligibility* stage. Our criteria revolved around six research questions that we collectively identified to be most pertinent to the topic, including 1) *what essential human values have been aligned by some AI models?* 2) *how did we effectively quantify or model human values to guide AI development?* 3) *what strategies have been employed to integrate human values into the AI development process?* 4) *how did existing studies improve human understanding and evaluation of AI alignment?* 5) *what are the practices for designing interfaces and interactions that facilitate human-AI collaboration?* 6) *How have AI been adapted to meet the needs of various human value groups?* We included papers that could potentially answer any of these questions. Further, based on the scope in Section 3.4, we excluded papers that did not meet our inclusion criteria. This resulted in a final corpus of 411 papers, which were analyzed in detail using qualitative coding (see Appendix A.4 for more details).

A.1.3 Qualitative Code Development. Referring to the code development process in Lee et al. [98], we first conducted qualitative coding for each paper by identifying relevant sentences that could answer the above research questions, and entering short codes to describe them into a codebook. We iteratively coded relevant sentences from each paper through a mix of inductive and deductive approaches, which allowed flexibility to expand, modify or change the driving research questions based on our learnings as we went through the process. To ensure rigor in our coding process, two authors coded each paper. The first author independently annotated all papers after reviewing the paper abstracts and introductions. Twelve team members each annotated a subset of the paper corpus. Our corpus includes papers from different domains (*e.g.*, HCI, NLP and ML). Therefore, we divided the authors into HCI and NLP/ML² teams and assigned the papers accordingly based on expertise. All team members coded each of their assigned papers to answer all six questions (if applicable) introduced above.

A.1.4 Framework Development and Rigorous Coding. After developing annotations, all authors collaborated to create the bidirectional human-AI alignment framework by integrating the annotations within each of the codes. The initial version of the framework was proposed by the author who reviewed all papers. This framework furthermore underwent iterative improvement through: 1) discussions with all team members involved in paper coding, and 2) revisions based

²Note that NLP and ML are two different domains, we combine them together for the purposes of literature review analysis since they both work on developing and evaluating AI technologies.

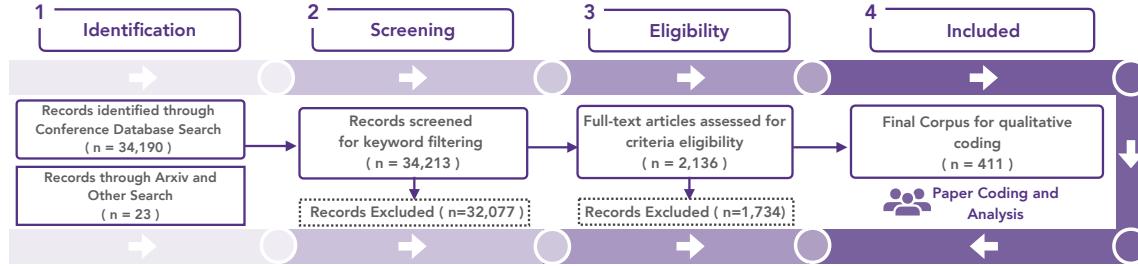


Fig. 7. The selection and refinement process of our systematic literature review. We referred to the PRISMA guideline [135, 186] to report the workflow. From the identification of 34,213 records by keyword search, to screen eligible papers against our criteria and arriveg at our final corpus of 411 papers. For each of the stages where literature reviews were excluded (identification, screening, and eligibility) we further present the total of excluded records.

on feedback from the project advisors. Additionally, we strengthened the framework by reviewing papers from the AI Ethics conferences (including FAccT and AIES), and related work of the collected papers that covered other domains such as psychology and social science. We further added missing codes and papers to ensure comprehensive coverage (see Appendix A.2 for details). The final bidirectional human-AI alignment framework, with detailed topologies, is presented in Section 4. Following the framework’s finalization, we conducted another separate coding process to annotate *whether each paper investigated dimensions within our framework*. Two authors independently coded each paper.³ These codes were then used to perform quantitative and qualitative analyses, as presented in Section 5.

A.2 Venues

We primarily focused on papers from the fields of HCI, NLP, and ML ranging from year 2019 to 2024 January. We included all their papers tracks (*e.g.*, CSCW Companion and Findings) without including workshops of conferences. From the ACL Anthology, OpenReview and ACM Digital Library, we retrieved 34,190 papers into a Reference Manager Tool (*i.e.*, Paperpile). Particularly, the venues we surveyed are listed below.

- **HCI:** CHI, CSCW, UIST, IUI;
- **NLP:** ACL, EMNLP, NAACL, Findings
- **ML:** ICLR, NeurIPS
- **Others:** ArXiv, FAccT, AIES, and other related work

Additionally, we also consolidate the framework by reviewing the papers published in FAccT and AIES (*i.e.*, important venues for AI Ethics research) between 2019 and 2024 and supplemented the codes, including the AI Regulatory and Policy code in Section 4.4.2 and the exemplary paper of Regulating ChatGPT [63]], which were not covered by the original collections. Also, we include a number of papers in the “Other” class are found by related work that are highly relevant to this topic.

A.3 Keywords

We decided on a list of keywords relevant to bidirectional human-AI alignment. The detailed keywords include:

- **Human:** Human, User, Agent, Cognition, Crowd
- **AI:** AI, Agent, Machine Learning, Neural Network, Algorithm, Model, Deep Learning, NLP

³The joint probability of agreement for the paper annotations was 0.78.

- **LLM:** Large Language Model, LLM, GPT, Generative, In-context Learning
- **Alignment:** Align, Alignment
- **Value:** Value, Principle
- **Trust:** Trust, Trustworthy
- **Interact:** Interact, Interaction, Interactive, Collaboration, Conversational
- **Visualize:** Visualization, Visualize
- **Explain:** Interpretability, Explain, Understand, Transparent
- **Evaluation:** Evaluate, Evaluation, Audit
- **Feedback:** Feedback
- **Ethics:** Bias, Fairness

A.4 Inclusion and Exclusion Criteria

To further filter the most relevant papers among the keyword-filtered 2136 papers, we identified the six most important research questions we are interested in. We primarily selected the potential papers that can potentially address these six questions after reviewing their title and abstracts. The six topics of research questions in our filtering include:

- RQ.1 **[human value category]** What essential human values have been aligned by some AI models?
- RQ.2 **[quantify human value]** How did we effectively quantify or model human values to guide AI development?
- RQ.3 **[integrate human value into AI]** What strategies have been employed to integrate human values into the AI development process?
- RQ.4 **[assess / explain AI regarding human values]** How did existing studies improve human understanding and evaluation of AI alignment?
- RQ.5 **[human-AI interaction techniques]** What are the practices for designing interfaces and interactions that facilitate human-AI collaboration?
- RQ.6 **[adapt AI for diverse human values]** How has AI been adapted to meet the needs of various human value groups?

Particularly, we provide elaborated inclusion and exclusion criteria during our paper selection as listed below. We are aware that we have limitations during our paper filtering process.

Inclusion Criteria:

- **[Human values]** we include papers that study human value definition, specification and evaluation in AI systems.
- **[AI development techniques]** We include techniques of developing AI that aim to be more consistent with human values with interactions along all AI development stages (e.g., data collection, model construction, etc.)
- **[AI evaluation, explanation and utilization]** we include papers that build human-AI interactive systems or conduct human studies to better evaluate, explain, and utilize AI systems.
- **[building dataset with human interaction]** especially responsible dataset.

Exclusion Criteria:

- **[Alignment not between human & AI]** we do not include alignment studies that are not between human and AI, such as entity alignment, cross-lingual alignment, cross-domain alignment, multi-modal alignment, token-environment alignment, etc.

- [AI models beyond LLMs - Modality] we do not focus on AI models other than LLMs (e.g., 3D models, VR/AR, voice assistant, spoken assistant), our primary model modality is text. Specifically, we do not consider audio / video data; we do not consider pure computer vision modality.
- [No human-AI interaction] we do not consider studies that do not involve the interaction between human and AI, such as (multi-agent) reinforcement learning. Specifically, we do not consider interactions via voices/speech, Do not consider game interaction; Do not consider interaction for Accessibility; Do not consider Mobile interaction; Not consider autonomous vehicle interaction wearable devices, or Physical interaction;
- [Tasks] art and design, emotion.
- [No human included]
- [focus on English] primarily focus on English as the main language;
- [Application] not include the NLP papers tailored for a specific traditional task, such as translation, entity recognition, sentiment analysis, knowledge graph, adversarial and defense, topic modeling, detecting AI generations, distillation, low resource, physical robots, text classification, games, image-based tasks, hate speech detection, Human Trafficking, etc.
- [Visualizing Embeddings] Visualizing/interacting transformer embeddings?
- [Embedding-based] explanation, evaluation, etc.
- [multi-agent reinforcement learning with self-play and population play] techniques, such as self-play (SP) or population play (PP), produce agents that overfit to their training partners and do not generalize well to humans.

We acknowledge the extensive scope and rapid advancements of research in this area, and posit that our study offers insights that can be generalized to various modalities. For example, the value taxonomy and human-in-the-loop evaluation paradigm outlined in our framework can be applied to both text-based and other modality-based (e.g., vision, robotics) models. It's worth noting that our literature review does not aim to exhaustively cover all papers in the field, which is impossible given the rapid advancement of human-AI alignment research. Instead, we adopt a human-centered perspective to review more than 400 key studies in this domain, focusing on delineating the framework landscape, identifying limitations, future directions, and a roadmap to pave the way for future research.

B AUTHOR CONTRIBUTIONS

This project was a team effort, built on countless contributions from everyone involved. To acknowledge individual authors' contributions and enable future inquiries to be directed appropriately, we followed the ACM's policy on authorship [130] and listed contributors for each part of the paper below.

B.1 Overall Author List and Contributions

Project Lead

The project lead initialized and organized the project, coordinated with all authors, participated in the entire manuscript.

- **Hua Shen (University of Michigan, huashen@umich.edu)**: Initiated and led the overall project, prepared weekly project meetings, filtered papers, designed dimensions and codes (initial, revision), coded all papers, initiated the framework and developed human value and interaction modes analysis figures, participated in drafting all sections, paper revision and polishing.

Team Leads

The team leads organized all team events, coordinated with leads and members, contributed to a portion of manuscript.

- **Tiffany Knearem (Google, tknearem@google.com)**: Led the HCI team, prepared weekly team meetings, filtered papers, designed dimensions and codes (initial, revision), coded partial papers, ideated the framework and analysis and future work content, participated in writing (Critical Thinking and AI Impact on Human sections), paper revision and polishing.
- **Reshma Ghosh (Microsoft, reshmighosh@microsoft.com)**: Led the NLP/AI team, prepared weekly team meetings, filtered papers, coded partial papers, ideated the framework and analysis and future work content, participated in writing (AI evaluation section), paper revision and polishing.

Team Members (Alphabetical)

The team members contributed to a portion of paper review, regular discussions, and drafted a portion of the manuscript.

- **Kenan Alkiek (University of Michigan, kalkiek@umich.edu)**: filtered papers, coded partial papers, data processing and analysis, ideated paper analysis and future work, paper revision and polishing, mainly involved in NLP Team
- **Kundan Krishna (Carnegie Mellon University, kundank@andrew.cmu.edu)**: filtered papers, coded partial papers, ideated the framework and future work, participated in writing (Customizing AI section), designed dimensions and codes (initial, revision), paper revision and polishing, mainly involved in NLP Team
- **Yachuan Liu (University of Michigan, yachuan@umich.edu)**: filtered papers, coded partial papers, participated in writing (revised Integrate General Value and Customization content sections), paper revision and polishing, mainly involved in NLP Team
- **Ziqiao Ma (University of Michigan, marstin@umich.edu)**: filtered papers, coded partial papers, designed dimensions and codes (initial, revision), developed Human Value category, participated in writing (Human Value taxonomy, revised representation, and value gap analysis sections), paper revision and polishing, mainly involved in NLP Team
- **Savvas Petridis (Google PAIR, petridis@google.com)**: filtered papers, coded partial papers, ideated the interaction-related analysis and future work, participated in writing (Perceive and Understand AI), paper revision and polishing, mainly involved in HCI Team
- **Yi-Hao Peng (Carnegie Mellon University, yihaop@cs.cmu.edu)**: filtered papers, coded partial papers, participated in writing (Human-AI Collaboration section), paper revision and polishing, mainly involved in HCI Team
- **Li Qiwei (University of Michigan, rrll@umich.edu)**: filtered papers, coded partial papers, ideated the interaction-related taxonomy and analysis, participated in writing (Interaction Mode section), mainly involved in HCI Team
- **Sushrita Rakshit (University of Michigan, sushrita@umich.edu)**: filtered papers, coded partial papers, participated in writing (Integrate General Value section), paper revision and polishing, mainly involved in NLP and HCI Team
- **Chenglei Si (Stanford University, clsi@stanford.edu)**: filtered papers, coded partial papers, designed dimensions and codes (initial, revision), ideated the framework and future work, participated in writing (Assessment of Collaboration and Impact section), paper revision and polishing, mainly involved in HCI Team

- **Yutong Xie (University of Michigan, yutxie@umich.edu)**: filtered papers, coded partial papers, designed dimensions and codes (initial, revision), ideated the value representation taxonomy, participated in writing (Human Value Representation section), paper revision and polishing, , mainly involved in NLP Team

Advisors (Alphabetical)

The advisors involved in and made intellectual contributions to essential components of the project and manuscript.

- **Jeffrey P. Bigham (Carnegie Mellon University, jbigham@cs.cmu.edu)**: contributed to the framework on aligning human to AI direction, vision on the status quo of alignment research, and future work discussions, and participated in paper revision and proofreading.
- **Frank Bentley (Google, fbentley@google.com)**: contributed to the historical context and project objectives, improved the definitions and design of research methodology, and participated in paper revision and proofreading.
- **Joyce Chai (University of Michigan, chaijy@umich.edu)**: iteratively involved in developing and revising definitions and the framework on aligning AI to human direction, advised on analysis and future work, and participated in paper revision and proofreading.
- **Zachary Lipton (Carnegie Mellon University, zlipton@cmu.edu)**: contributed insights from Machine Learning, NLP, and AI fields to revise the definitions and framework on aligning AI to human direction, and participated in paper revision and proofreading.
- **Qiaozhu Mei (University of Michigan, qmei@umich.edu)**: contributed insights from Data Science, Machine Learning, and NLP fields to improve definitions and the framework on aligning AI to human direction, and participated in paper revision and proofreading.
- **Rada Mihalcea (University of Michigan, mihalcea@umich.edu)**: involved in framing and revising the structure and taxonomy of human values, and contributed to improving the manuscript's title, introduction, and other sections, and participated in paper revision and proofreading.
- **Michael Terry (Google Research, michaelterry@google.com)**: contributed arguments and vision on the status quo of alignment research, framed project objectives and contributions, improved definitions and data analysis, and participated in paper revision and proofreading.
- **Diyi Yang (Stanford University, diyiy@stanford.edu)**: involved in improving definitions and the framework, contributed social insights to the work, and participated in paper revision and proofreading.

Project Leading Advisors

The project leading advisors actively involved in the entire project process and all manuscript sections.

- **Meredith Ringel Morris (Google DeepMind, merrie@google.com)**: iteratively involved in drafting all sections, contributed to core argument ideation, framework and definition improvement, provided future work insights, and participated in paper drafting, revision, and proofreading on all sections.
- **Paul Resnick (University of Michigan, presnick@umich.edu)**: actively involved and advised on the entire project process, including initiating the project and research agenda, iteratively improved definitions, framework, and analysis, and participated in paper revision and proofreading.
- **David Jurgens (University of Michigan, jurgens@umich.edu)**: provided advice throughout the project, including iterative discussions on project milestones and content ideation, organized several meetings to receive feedback from external audiences, and participated in paper revision and proofreading.

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