1 Introduction: "We're Doing Something Completely New"

On April 29, 2022, the Human Computation Institute hosted a live event for the final hour of their so-called Catchathon. For this special 24-hour event, the institute invited participants, schoolchildren, libraries, and the general public to join a timed competition taking place within the human computation (HC)–based citizen science (CS) game Stall Catchers. The participants' task consisted of analyzing Alzheimer's disease research data presented as short video sequences in a gamified setting on the Stall Catchers platform. In doing so, they checked the blood vessels depicted in the videos for blockages, annotating them as either "flowing," or "stalled" if they detected a blockage or "stall" in the blood flow. Within this competition format, teams of participants competed against each other aiming to annotate the highest number of research videos by the end of the competition. In this specific Catchathon, they also competed against the artificial intelligence (AI) bot GAIA.

During the final-hour event hosted on Zoom, joined by several classes of students from Miami along with other participants from around the world, Pietro Michelucci, the director of the institute and Stall Catchers project lead, summarized this Catchathon competition: "GAIA is fast, but not quite as skillful as" (Human Computation Institute 2021, 32:28–32:31) Stall Catchers' best human participants. While the institute had previously organized several such Catchathons, this competition was unique: "We're doing something completely new" (Human Computation Institute 2021, 17:36–17:40). In addition to the human crowd participating in the competition, the "intelligent bot," as it was called on the institute's blog (Egle [Seplute] 2021c), or the "artificial intelligence agent" (Human Computation Institute 2021, 18:15–18:17) GAIA analyzed research videos alongside human participants. Not knowing how human participants would respond to and engage with the bot and how these new participant–bot relations would unfold, the Stall Catchers team had worked hard on building a "bot-wrapper" to introduce what appeared to be the very first "world's citizen science bot" (Human Computation Institute 2021, 18:10–18:12).[1] Named after the primordial goddess in Greek mythology, the personifica-

1 This included the development of an application programming interface (API) to allow the machine learning (ML) model to communicate with the Stall Catchers platform and bot–user profiles

tion of Earth, GAIA was trained on human participants' annotation data and built using techniques from deep learning (DL) employed to play Stall Catchers.

Michelucci assessed GAIA's performance as good, although not exceeding some human participants' skill levels. This assessment seemingly also reflected some relief after one participant referred to GAIA as a "pesky bot" (Egle [Seplute] 2021c) capable of annotating research videos all night, while most of the human participants slept. The institute's blog post summarizing the final statistics of the Catchathon eventually stated that, even though it was a "close race," "it's 1 for supercatchers, 0 for GAIA [robot emoji], eh? [emoji with a winking face and tongue sticking out] Just kidding—we're all in this together, GAIA [robot emoji] included, and hopefully she will help us analyze data faster in the future!" (Egle [Seplute] 2021c). The experiment, therefore, succeeded, demonstrating that a bot such as GAIA could be successfully introduced to the platform without completely outpacing and beating human participants. Instead, this introduction stimulated competition.

Stall Catchers, aimed at advancing the Alzheimer's disease research conducted at the Schaffer–Nishimura Lab in biomedical engineering at Cornell University, was created to solve a specific data analysis problem that could not be solved by the laboratory's researchers nor via computational methods alone. The introduction of GAIA into Stall Catchers kicked off the Human Computation Institute's ongoing research into how human participants and AI bots could be combined to not only speed up analysis, but also ensure the scientifically required quality of crowdsourced answers (or, simply, crowd answers). Even without AI bots, Stall Catchers relies on a complex "wisdom-of-the-crowd" approach (Surowiecki 2005) to calculate crowd answers from individual participant's video annotations. This approach itself relies on nontrivial human–technology,[2] human–software or human–algorithm relations, which together form the core of the HC system Stall Catchers.

The Human Computation Institute followed an HC approach, combining humans and computers in new ways to solve the data analysis problem. While participant–software relations had thus far relied on humans performing the actual data analysis with algorithms consigned to evaluating and combining human inputs, the introduction of AI bots to the regular Stall Catchers game would alter these relations. Creating partnerships between humans and AI bots (Vaicaityte 2021a), for instance, would redistribute human and software roles and shift the respective responsibilities in this sociotechnical system. These human–technology relations, however, do not simply rely upon and come into being based solely on the designers' and developers' imaginations, decisions, and implementations. Instead, they depend just as much upon participants' active engagement and adoptions, alongside technological affordances (Gibson 1977; 1979; Bareither 2020a) and action potentials, which only become actualized through usage and practice (Beck 1997). Together, these human and nonhuman actors form dynamic and contingent

allowing ML models to become part of the game. This also included adapting the platform and improving its resilience to anticipate increased traffic during the event.

2 Human–technology relations here do not suggest any order between humans and technology but represent different relations, such as human–human, technology–human or human–technology–human relations.

relations which together create the HC-based CS system. This first encounter between human participants and AI bots serves as a salient and illustrative moment in Stall Catchers' evolution, given that it introduces new forward movements within its participant–AI relations. I call these movements involving the redistribution of agency, shifts in the role assignments of subjects and objects, and reconfigurations of tasks and practices between human and nonhuman actors *intraversions*.

Fundamentally, this book concerns HC-based CS projects such as Stall Catchers as sociotechnical assemblages and the human–technology relations unfolding within them and simultaneously forming them. The assemblage concept was originally proposed by philosopher Gilles Deleuze and psychoanalyst Félix Guattari (2013), and subsequently further defined and developed by different scholars with various foci and without always strictly following Deleuze and Guattari's thinking (e.g., Law 2004; DeLanda 2006; 2016; Ong and Collier 2005; Brenner, Madden, and Wachsmuth 2011; Buchanan 2015). While I discuss the concept in detail in Chapter 2, assemblages can be broadly defined as temporally consistent and volatile compositions of heterogeneous elements, such as human and nonhuman actors, and their relations, temporarily coming together and forming certain configurations from which assemblages emerge that go beyond the sum of the individual elements (Welz 2021a, 161). I analyze how HC systems in the field of CS are formed in the interplay of different human—such as developers, scientists, and participants—and nonhuman (or more-than-human)[3] actors to determine how they are 1) imagined and developed as new forms of *hybrid intelligence* (HI) and 2), at the same time, negotiated in everyday life and ethical practice in the entanglements of play and science. 3) I investigate the role of trust in the continuous formation processes. Building upon this, I focus on how human–technology relations unfold within this complex interplay and these negotiations, as well as how they continuously transform through future thinking, everyday adaptations, and failures. Thus, I follow an analytical approach that focuses on the becoming (Hultin 2019) of human–technology relations and HC-based CS assem-

3 With the aims of moving past the divide between nature and culture, decentering the human, and "get[ting] non-humans to speak as more than spokespersons for human interests" (Latimer and Miele 2013, 7), ecological, anthropological, science and technology studies (STS), feminist, and other programs turned to naturecultures and more-than-human approaches (*cf.*, e.g., Gesing et al. 2019; Welz 2021b). The philosopher, anthropologist, and sociologist Bruno Latour has aptly shown in his book *We Have Never Been Modern*, aiming to reconnect nature and culture, that the divide is a modern invention that cannot hold (1993). I discuss actor–network theory's (ANT) role in these discussions and its symmetric ontology in Chapter 2. Taking it a step further, the biologist, philosopher of science, and feminist theorist Donna Haraway, in *The Companion Species Manifesto*, describes the aim of the manifesto's agenda as follows: "Cyborgs and companion species each bring together the human and non-human, the organic and technological, carbon and silicon, freedom and structure, history and myth, the rich and the poor, the state and the subject, diversity and depletion, modernity and postmodernity, and nature and culture in unexpected ways" (2003, 4). Today, these pathbreaking conceptual shifts have gained much support across research programs, as stated above. In this work, I discuss humans and nonhumans, or human and nonhuman actors, and further specify, whenever possible, who and what are acting and engaging with each other in which relation.

blages that, with the concept of intraversions (see below), considers both instantaneous situations and historical becoming.[4]

As the example of the Catchathon has already shown, different human actors—including the institute's designers and developers, the volunteer participants, and the biomedical researchers—come together and contribute to form the assemblage. They do so not only by engaging in relations with other humans, but also (indirectly or directly, depending on their role) with nonhuman actors. I consider nonhuman actors as including materialities, such as infrastructure and microscopes, along with other entities such as data, algorithms, user interfaces (UIs), AI bots, and mice. I refer to nonhuman actors stressing that they are neither neutral nor passive objects only acted upon. Nevertheless, and following physicist and feminist theorist Karen Barad's understanding (1996, 181), I consider human and nonhuman agency asymmetrical. The different but interwoven human–technology relations resulting from the engagement of human and nonhuman actors continuously lead to the becoming of Stall Catchers, which, in turn, (re)configures the relations embedded within it. This becoming of the assemblage is simultaneously situated in a space which is both productive and features tensions because of the different affordances, expectations, and goals associated with play and science in CS games. Additionally, various processes impact the assemblages, bringing them closer together or tearing them apart. One example of such processes affecting HC-based CS assemblages, which I observed during my research, is trust. As my analysis shows, trust and trust-building mechanisms emerge and must be adapted alongside the intraverting relations in HC-based CS.

Thus, I employ the concept of *intraversions* to describe how human–technology relations in HC-based CS projects unfold in everyday life and develop continuously over time. As a concept, intraversions refer to the processual forward movements and shifts within relations between humans and technology. These movements and shifts result from the introduction of new computational capabilities and through the potential arising from existing relations directly forming based on human actors' practices or algorithmic and material affordances. Various forms of reconfigurations occur along the processual forward movements within human–technology relations. These include 1) shifts in the role assignments of subjects and objects—or, more precisely, in the distributed agency across the different actors—, which can never be fully attributed to one side or another; or 2) redistributions of tasks or practices. Intraversions take place along two dimensions: via instantaneous interactions—or intraactions (Barad 1996)—and via gradual temporal developments, thereby justifying why they must always be analyzed in and across time. Following this understanding, power dynamics are also not fixed in time, but change with these reconfigurations.

4 Emergence-theoretic approaches, like ANT, which emphasize specific moments, have faced criticism for overlooking the historical and societal embeddedness of phenomena (Hinrichs, Röthl, and Seifert 2021, 93; Wietschorke 2021, 57). While other scholars have stressed that ANT does, in fact, include processualism as one of its theoretical dimensions (Belliger and Krieger 2006, 24), using the concept intraversions, I aim to provide an analytical and heuristic tool that overcomes the risk of neglecting these formative factors.

Intraversion, in contrast to inversion, does not merely mean that the exact opposite of what previously existed emerges (this may be possible, but is not a necessary or defining characteristic). Instead, intraversions describe cyclical modifications that build upon previous instances of relations and are, thus, always connected to the past while generating something new. If assigned subject/object positions, for instance, at some point flip back to a previous constellation, they are, nevertheless, not the same as they were previously. A simplified general example is as follows: An AI model was first used to analyze specific data and the human participants' task was to review the result, followed by a new task distribution where the human's task was to analyze the data while the result was reviewed by a computational model (because the previous AI model did not perform sufficiently well on the analysis), in order to ultimately retrain the AI model to take over the analysis once again; the relation emerging from this constellation differs from its first iteration. This is because the AI model and human participant are no longer the same in this new relation (e.g., the AI model *learns* from the human participants and the participants change their practices in working with an *improved* AI model). In this example, tasks and subjectivities are not merely swapped, but transformed or generated anew.

The concept of intraversions is conceptualized by building upon and drawing from a combination of existing theoretical approaches, which I outline in detail in Chapter 2, to derive an analytical and heuristic tool that contributes a specific focus on changing human–technology relations in HC systems. I employ Barad's understanding of intraactions which, instead of referring to interactions between fixed and independent entities, moves beyond such dichotomies (1996, 179). According to this understanding, humans and technologies can never be considered independent of each other, but instead are co-constituted in relations. Accordingly, responsibilities and power are understood in the Foucauldian sense as things that do not belong to one party or actor, but are distributed and move across these relations (Foucault 1998).

The notion of intraversions emerged during the analysis of my empirical material of HC-based CS when I attempted to understand how human–technology relations in the projects I studied evolve and unfold in everyday life. The fact that they continuously change became clear quite early: HC-based CS projects are created to solve a specific (scientific) problem that cannot be solved with current AI capabilities only, relying instead on new interplays between humans and computational or AI entities to do so. Thus, these projects necessarily must evolve alongside AI developments to remain at the edge of AI and scientific problem solving. They, and specifically their human–technology relations, must stay (and are intentionally pushed) open for future tweaking and changes. The relations' intraversions are, therefore, imagined by different actors, particularly by designers and developers. However, intraversions are also material, situational, and contingent, and guided by the encounter of different actors and a continual attempt to structure these human–technology relations differently. From this emerges resistance, counteractions, and failings, along with variously ascribed meanings;[5] intraverting relations, then, are multiples (Mol 2002b).

5 I am interested in the everyday meanings actors ascribe to the HC-based CS systems studied when referring to "meaning" (Beck 1997, 14).

In this work, I analyze intraversions of human–technology relations in HC-based CS projects designed as games or so-called "games with a purpose" (GWAPs) (Von Ahn 2005). The intraversions observed are, thus, specific to the context of HC and the play/science "interferences" (Dippel and Fizek 2017a; 2019) in which they emerge. Returning to the AI bot example, the possibility of including AI bots in the Stall Catchers game only emerged from previous participant–software relations, which, at some point, enabled the training of AI models on data generated by participants. Subsequently, when wrapped in a bot participant on Stall Catchers (identifiable for participants by its username and bot icon on the leaderboard), AI models became new subjects in the game. Instead of human participants' performances being merely evaluated by computational tools in the background, software is now perceived as another fellow participant or, as I show in Chapter 6, as a competitor.

In addition to examining the intricate entanglements of play and science, analyzing human–technology relations in HC-based CS assemblages necessitates a comprehensive understanding of the broader field of HC and its overarching goals and visions. I, therefore, now turn to a brief overview of the emergence and historical development of HC. This overview is intended to provide a foundational understanding of the field before I shift to its current state of the art and how it relates to other areas of AI research.

According to computer scientists Alexander Quinn and Benjamin Bederson (2011), HC can be situated in the history of AI research beginning from the 1950s. They refer to mathematician, logician, computer scientist, and cryptanalyst Alan Turing's article "Computing Machinery and Intelligence" (1950) and computer scientist and psychologist Joseph Carl Robnett Licklider's "Man–Computer Symbiosis" (1960) as examples of the interconnectedness between HC and machine computation (Quinn and Bederson 2011, 1403). However, scholars only began thoroughly investigating the idea in the early twenty-first century (Quinn and Bederson 2011, 1403). One of the first HC systems was the "completely automated public Turing test to tell computers and humans apart" (CAPTCHA), developed in 2000 by computer scientist Luis Von Ahn and colleagues at Carnegie Mellon University in Pittsburgh (Von Ahn 2005). CAPTCHA was created as a security mechanism on the Internet to block programs and bots from accessing platforms and Internet services by asking users to recognize and correctly type a distorted word. This task proved simple for humans, while it was unsolvable for computer programs. Note that humans, here, are understood as seeing and without visual impairment.

CAPTCHAs were also considered free cognitive workers (Aytes 2012, 79). In 2010, about 200 million such CAPTCHAs were completed daily worldwide, which, at ten seconds per CAPTCHA, equated to about 500,000 hours of human work per day (Von Ahn 2010). Von Ahn explained in a presentation at the US National Science Foundation that this figure prompted him to think about how CAPTCHA could be used for something "good;" after all, it is not only valuable human time, but also a valuable activity computers could not simply take over (Von Ahn 2010). As a result, scientific research at Carnegie Mellon University gave rise to the reCAPTCHA project, subsequently purchased by Google (Google, n.d.), which now used these access restrictions to digitize books and train AI using data. By presenting people with images or words, one part of which is machine "known" or readable with the other part remaining unknown, reCAPTCHA checks whether it is a human completing the reCAPTCHA. At the same time, it "learns" a new word. The same task is presented to several people and their answers are combined to ensure that the word or image is correctly annotated or recognized. The paradox of reCAPTCHA is that a computer program initially creates a task for humans that it cannot solve itself, but simultaneously checks whether humans solve the task correctly.

However, these relations between humans and software are not fixed, because even reCAPTCHAs are constantly changing with the emergence of new machine solutions and user tactics aimed at automatically bypassing such tests.[6] I refer to such changes as *intraversions*. While Internet users contributed to reCAPTCHA because they had no choice, Von Ahn soon developed the first computer games building upon the HC approach in his doctoral thesis in 2005, introducing GWAPs (2005). In his dissertation, Von Ahn likely first defined[7] the term *human computation*[8] in its current understanding in HC research as "a paradigm for utilizing human processing power to solve problems that computers cannot yet solve" (2005, 3). In a later book Von Ahn published together with Edith Law, they further specify HC as "a new and evolving research area that centers around harnessing human intelligence to solve computational problems [...] that are beyond the scope of existing Artificial Intelligence (AI) algorithms" (Law and Von Ahn 2011, xv). Compared to Von Ahn's first definition, they now specifically situate HC within AI research, using a definition that can be understood as minimal, and upon which most HC proponents appear to agree. At the core of HC research lies the combination of humans—or to be more precise, human *intelligence* (see above) or *cognition* (Michelucci et al. 2015, 2)—and computational systems.

Aiming to define and distinguish HC from other concepts that build upon a "wisdom-of-the-crowd" approach like Wikipedia, Law and Von Ahn revisit computer science understandings of computation and algorithm (Law 2011; Law and Von Ahn 2011). Building on the perception of computation as "the process of mapping of some input representation to some output representation using a explicit, finite set of instructions (i.e., an

6 See, for example, the list of practices to bypass CAPTCHAs in the digital publication "HackTricks" by Carlos Polop (n.d.). On a website regarding CAPTCHA by Carnegie Mellon University, CAPTCHAs are described as a win–win situation since, even if they were broken by malicious users, this would have the advantage of solving an AI problem: "CAPTCHA tests are based on open problems in artificial intelligence (AI): decoding images of distorted text, for instance, is well beyond the capabilities of modern computers. Therefore, CAPTCHAs also offer well-defined challenges for the AI community, and induce security researchers, as well as otherwise malicious programmers, to work on advancing the field of AI. CAPTCHAs are, thus, a win–win situation: either a CAPTCHA is not broken and there is a way to differentiate humans from computers, or the CAPTCHA is broken and an AI problem is solved" (Carnegie Mellon University, n.d.). From the perspective of HC, subversive or malicious practices were, thus, considered an AI advancement rather than a problem. However, this understanding might not be shared by service providers on the Internet who rely on CAPTCHA as a security measure.

7 Computer scientist Edith Law refers to 2006 as the year in which HC was first coined (2011).

8 The term "human computation" forms an interesting return to the term "computer" as used beginning in the 1600s, where "computers" referred to humans performing calculations (Grier 2013). In the twentieth century, "human computers" were mostly women, who "were the computational processors behind everything" (Gray and Suri 2019, 52), including, for example, supporting the US in World War II and in space exploration (Light 1999; Holt 2016).

algorithm)" (Law 2011, 2, emphasis i.o.), Law and Von Ahn specify HC as "intelligent systems that explicitly organize[ ] human efforts to carry out the process of computation – whether it be performing the basic operations, or taking charge of the control process itself (e.g., specifying what operations need to be performed and in what order)" (Law 2011, 2). In addition, they build upon "explicit control" as an important element of HC systems. Explicit control here refers to the notion that the computation is a direct result of a predetermined algorithm, controlled by either humans or computers (Law 2011, 3). Applying this definition, Law and Von Ahn frame HC based on the ideas of, on the one hand, people being "engaged to perform meaningful tasks through some other activities that they are already deeply interested in (e.g., playing games, signing up for email accounts)" (Law 2011, 1), such as in GWAPs or in reCAPTCHA. However, I would argue, people are probably engaged in the latter example because they cannot avoid it. On the other hand, computations are always controlled to accurately and efficiently solve a problem addressed (Law 2011, 1). While an understanding of HC systems as "purposeful" is shared as a key concept to HC by various advocates, including Michelucci (e.g., 2013d, 84), the purpose does not necessarily refer to an individual's enjoyment, but can instead refer to results "that derive from collective behavior or interactions, such as the advancement of science that results from citizen science projects" (Michelucci 2013d, 84).

There have also been numerous attempts to differentiate HC from other terms like crowdsourcing, human-based computation, organismic or social computing, and collective intelligence (for different taxonomies, see, for example, Quinn and Bederson 2011; Michelucci 2013d; Newman 2014). At times, these terms are used synonymously, while at other times controversy arises, illustrating the fuzzy concept of HC and the numerous attempts to delineate the boundaries of this emerging field.

While the first years of HC were characterized by individual researchers, the first Human Computation Workshop (HCOMP 2009) took place in Paris, France, in 2009, bringing together "a wide variety of perspectives" (Ipeirotis, Chandrasekar, and Bennett 2009) from different disciplines (Quinn and Bederson 2011, 1403). Less than ten years after the first mention of HC in Von Ahn's doctoral thesis, researchers from the fields of AI, art, genetic algorithms, cryptography, and human–computer interaction—each field itself describing interdisciplinary fields—contributed to HC research (Quinn and Bederson 2011, 1403). The Association for the Advancement of Artificial Intelligence (AAAI) Conference on Human Computation and Crowdsourcing (HCOMP) was first organized in 2013 in Palm Springs, California, as a new space to bring together these different disciplines and researchers in a recurring format, which has since taken place annually.[9] The first conference covered topics and research ranging from human–computer interaction to cognitive psychology, economics, and various fields of AI. While the overlap with AI research is rather broad, according to the co-chairs, HCOMP extends beyond AI research. "[H]uman computation promises to play an important role in research on principles of artificial intelligence as well as in the engineering of systems that can take

9 However, critical scholars, science and technology studies researchers, and cultural anthropologists, for example, seem to be missing or, at least, do not yet appear represented within this interdisciplinary conference.

advantage of the (changing) complementarities of human and machine intellect" (Hartman and Horvitz 2013, xi). Pointing to the interdisciplinary nature of the new research area of HC, the co-chairs aimed to highlight the context, field, and attention HC gained over the years. Despite the domination of hard science perspectives, varied disciplinary perspectives and approaches to knowledge production come together in the discourse on HC. Conceivably, the diversity reflected in the various definitions of HC is, to some extent, explained by these varied traditions and epistemologies.

Following the publication of Von Ahn and Law's book *Human Computation* in 2011, the field witnessed another significant contribution with the publication of *Handbook of Human Computation*. Edited by Michelucci and published in 2013, this handbook presented a more extensive and broader approach to the field of HC (Michelucci 2013a). One specific aim of the handbook was to further broaden the interdisciplinarity of HC. This, for example, manifests itself in the preface written by cultural anthropologist Mary Catherine Bateson. The handbook includes chapters from both scientists and practitioners as well as visionaries in the field, offering the most comprehensive collection of different perspectives on HC to date. Only one year later, Michelucci established the transdisciplinary *Human Computation Journal*, the first journal dedicated specifically to HC, which further contributes to the HC discourse by continuing to publish research in the field, thereby accompanying and steering the developments in HC research (Michelucci and Gadiraju, n.d.).

Beyond organizing conferences dedicated to HC and the publications mentioned, the field appears to have gained further attention in recent years with the term "hybrid intelligence." In the HI literature, combining the skills of humans and machines or AI aims not only "to collectively achieve superior results" (Dellermann, Calma, et al. 2019, 276), but to also ensure that both "continuously improve by learning from each other" (Dellermann, Calma, et al. 2019, 274). Not only have research institutes named after HI been founded over the years (e.g., Elmann 2022; The Hybrid Intelligence Centre, n.d.) and the first HI conferences organized (Humane AI Net; The Hybrid Intelligence Centre, n.d.), but startups and companies such as McKinsey also seem to claim the term for their approach to AI, understanding HI as the "future of artificial intelligence at McKinsey" (McKinsey 2022). While definitions for HC and HI may vary and their research agendas sometimes focus on different aspects, considerable overlap remains in the understanding of HC and HI. In addition, researchers in these fields often employ similar approaches. Consequently, given these commonalities, I often discuss HC and HI together within my research (and "HC" can mostly be read as "HC and HI"); however, in general, they should not be considered as completely synonymous.[10]

If we now look at existing HC systems, in a broad sense they appear in various fields of everyday life, such as within access control systems for web services in the case of reCaptcha or in crowdworking platforms such as Amazon Mechanical Turk (Amazon Mechanical Turk, Inc., n.d.) and Clickworker (Clickworker GmbH, n.d.), where humans are monetarily compensated for completing so-called microtasks (Gray and Suri 2019). Microtasks can be understood as a "contemporary instantiation of piecework" (Alkhatib,

10 A more detailed definition of HI and how its development as a research field relates to HC is provided in Chapter 4.

Bernstein, and Levi 2017, 4609). HC systems can also be found in digital CS projects, such as Stall Catchers in which participants voluntarily contribute and where the form of involvement primarily relies on initialization from researchers, HC designers, and developers.

In general, the development of HC systems closely aligns with that of AI. In more recent years, AI has witnessed significant achievements, providing numerous examples of machines outperforming humans given their incomparable speed, accuracy, and tremendous memory. A recent example from natural language processing (NLP) lies in OpenAI's ChatGPT (OpenAI, n.d.) (along with the subsequent surge of models it inspired, including Anthropic's Claude [Anthropic PBC, n.d.] and Meta's LLaMa [Meta 2023.; *cf.* Touvron et al. 2023]). ChatGPT is a conversational model that builds upon DL and reinforcement learning from human feedback to generate outputs often indistinguishable from human responses, usually capable of performing complex, advanced tasks such as writing code, creating poetry or solving reasoning problems. Other domains include OpenAI's DALL-E (OpenAI, n.d.; *cf.* Ramesh et al. 2021; 2022) and CompVis Ludwig Maximilian University (LMU)'s Stable Diffusion developed together with Stability.AI (Rombach et al. 2022). Both of these represent DL models that generate digital images from natural language prompts. In addition, DeepMind's AlphaFold (EMBL-EBI, n.d.; *cf.* Jumper et al. 2021), is a high-performance AI system that can predict three-dimensional (3D) protein structures from amino acid sequences.

Despite these advancements, however, AI-based computer algorithms and models often still face fundamental limitations in tasks such as mathematical reasoning and some comparatively basic problems easily solved by humans like planning and creative thinking (Bry, Schefels, and Wieser 2018; Bubeck et al. 2023). Furthermore, the limitations of current AI systems repeatedly become apparent when the promises of new approaches remain unfulfilled or AI systems demonstrate their ability to cause real societal harm, such as in the field of law enforcement with the example of predictive policing (e.g., Brayne 2017; Ferguson 2017; McDaniel and Pease 2021). In addition, even where AI systems appear to solve complex problems with a high accuracy (and, in fact, may do so), the problem remains that most AI systems, especially the most *successful* ones often based on DL, are effectively black boxes whose outputs cannot be easily explained and whose accuracy is difficult to verify. Today's large language models (LLMs) are specifically known to perform well, producing *confident* responses, while unreliably discerning true facts from plausible fiction in doing so. Research directions in the field of AI generally aim to develop a strictly computational AI, often in pursuit of *strong AI* and *artificial general intelligence* (AGI). Such developments, at some point, are expected to achieve *human-like intelligence*, or at least *weak AI*, which aims to develop systems with superhuman performance targeting specific, albeit limited tasks. By contrast, HC pursues the goal of combining the respective strengths of humans and machines to realize unprecedented capabilities (Michelucci and Simperl 2014, 1). Human Computation is guided by the idea that combining humans and machines can solve complex problems for which no solutions currently exist with either *merely* computational or *merely* manual human approaches.

In the Stall Catchers example, the problem to solve was the data analysis problem that biomedical researchers at the Schaffer–Nishimura Lab faced in their Alzheimer's disease research. Building on a biomedical understanding of Alzheimer's disease based on the understanding of neuropathological changes in the brain as causing disease—an approach medical anthropologist Margaret Lock refers to as "localization theory" (2013)—researchers study the reasons for the decreased blood flow in Alzheimer's disease using genetically engineered mice.[11] In their previous work, they found that blockages or stalls in capillaries, the smallest blood vessels, occurred in mice with Alzheimer's disease ten times more often than in mice without the disease, generally leading to a 30 percent reduction in the brain's blood flow (Egle [Seplute] 2018; *cf.* Bracko et al. 2019; Ali et al. 2021). This decreased blood flow, also associated with Alzheimer's disease in humans, could also lead to an accumulation of amyloid beta, which is likely partly responsible for characteristic Alzheimer's symptoms. To understand the reduced blood flow better and how it can be ameliorated, researchers take *in vivo* images from the brains of mice using highly advanced fluorescence microscopy techniques.[12] The images acquired must be thoroughly analyzed individually, which, given the amount of data generated, is a tedious and time-consuming task. Eventually, this process led to a backlog of data to be analyzed, substantially slowing down the research process.

The laboratory's attempt to automate the image analysis using ML algorithms was unsuccessful because no model at that time achieved the data quality and accuracy required. This problem provided the perfect opportunity to build an HC-based CS project for cognitive scientist, mathematical psychologist, and founder of the Human Computation Institute Michelucci, via which to explore and develop "novel methods leveraging the

11 I do not specifically focus on mice or build upon the interdisciplinary field of human–animal studies (DeMello 2021) in my research, even though such studies play a fundamental role in Alzheimer's disease research conducted at the biomedical laboratory and, thus, in the Stall Catchers project. In fact, Stall Catchers would not exist without mice. However, such a focus lies beyond the scope of this study due to my research interest, which focuses on HC, and specifically on HC-based CS games and their human–technology relations, which do not necessarily include animal research. Furthermore, to ensure the feasibility of my research, I needed to draw boundaries around the Stall Catchers assemblage studied. In this research, mice are, therefore, mostly present in the form of digital research data. Mouse models, nevertheless, played an important role during my fieldwork at the laboratory, since most research practices related to Stall Catchers involved mice, including caring for mice, performing surgeries on them, doing experiments with them, and, in the end, also euthanizing mice. Conducting participant observation on these practices was challenging for me and it became a topic of conversation with various members of the laboratory and the Human Computation Institute. Research with animals is controversially discussed in the public and scientific discourses, and my research partners were aware of that. They cared for the animals, at times beyond the requirements in various guidelines and ethical regulations.

12 Fluorescence microscopy is a technique in which expressed fluorescent proteins or administered small molecule fluorophores are excited with a specific wavelength; during recovery into their energy ground state, they emit a photon of a defined higher wavelength. Two-photon imaging was most commonly used for *in vivo* mouse studies (Denk, Strickler, and Webb 1990; Palikaras and Tavernarakis 2015). In two-photon imaging, two photons of lower energy—for example, near-infrared light—are used to achieve the excitation of fluorophores. The use of low-energy near-infrared light and a good tissue penetration allows for the imaging of a thick specimen and even living tissue. Researchers at the Schaffer–Nishimura Lab primarily used two-photon microscopy for Alzheimer's disease research, although the laboratory also had a microscope for three-photon microscopy.

complementary strengths of networked humans and machines" (Human Computation Institute, n.d.). Coincidentally, Michelucci was searching for a problem to solve using HC at that time. Researchers hoped that this new project could solve their data analysis problem by combining a crowd of volunteer participants performing analytical tasks alongside computer algorithms that tracked and evaluated each individual participant's contribution and calculated and finalized crowd answers by combining them. Stall Catchers is, thus, an example of how HC systems rely on humans and algorithms to jointly tackle problems neither can easily solve on their own. They do so by delegating specific computational steps or tasks to humans "in the loop." These computational tasks can range from classification tasks, as is the case in Stall Catchers, to taking over complex design tasks (e.g., Center for Game Science [University of Washington] et al., n.d.a). Human computation systems, therefore, can assume various configurations regarding how humans are invited to contribute.

Starting from current scientific and AI problems, HC remains at the edge of AI and, as such, must continuously adapt to new developments in AI, while simultaneously also influencing these developments (albeit indirectly). Human Computation, like HI, not only begins with current AI problems, but also actively distances itself from other AI research approaches: "Research in the field of Artificial Intelligence seeks to model and emulate human intelligence using a machine. Research in human computation leverages *actual* human intelligence to perform computationally-difficult tasks" (Crouser, Hescott, and Chang 2014, 48). Representatives of HC even view it as a *better* alternative for the development of a "superior intelligence" (Michelucci 2016, 5). Due to this ethical framing of HC in the field of HC-based CS, I consider the development of HC systems "ethical projects" (Ege and Moser 2021a), since they are "future-oriented undertakings" (Ege and Moser 2021a, 7) that strive for "better" human–AI systems. The concepts of "sociotechnical imaginaries" (Jasanoff and Kim 2015), and philosopher of ethics and technology Steven Dorrestijn's "subjectivation and technical mediation" (2012a), which he develops following philosopher Michel Foucault, provide further helpful theoretical approaches to analyze how HC-based CS systems are imagined and how human actors relate to, shape, and are shaped by them.

As "laboratories" for exploring new human–technology relations of the future, HC-based CS forms a particularly fruitful research field for cultural anthropological analysis. In particular, designers and developers of these sociotechnical systems do not pursue the goal of developing a system that at some point is complete, but instead focus on tackling specific scientific problems and move on to new challenges once a solution is found. In this sense, human–technology relations, as well as the sociotechnical systems themselves and their purposes remain open and continuously changing. Projects range from astronomy and biochemistry to flood prediction and art history.[13] In general, CS is commonly understood as "the active engagement of the general public in scientific research tasks" (Vohland et al. 2021, 1). The term itself has become an umbrella (Wiggins and Wilbanks 2019, 5) for various kinds of public involvement in scientific projects,

13 See, for example, Stardust@home (Westphal et al. 2005; Stardust@home, n.d.), Foldit (Center for Game Science [University of Washington] et al., n.d.a), UpRiver (Suarez 2015), and ARTigo (Ludwig-Maximilians-Universität n.d.).

allowing "citizen" scientists without professional training to collaborate with academic researchers in various ways and at all stages of the scientific process, primarily contributing to data collection and data analysis.[14] In my research, I focus on CS initiated by professional scientists themselves, and more specifically on online and digital CS, to which participants can contribute using their own computers or mobile devices. Most projects in the field of HC-based CS are designed as GWAPs, in which "players perform a useful computation as a side effect of enjoyable game play" (Von Ahn and Dabbish 2008, 61). This "useful computation" often both directly serves to advance the scientific research behind the game and the development of AI models to solve the underlying problems, while simultaneously allowing participants to contribute to scientific research and enjoy the games. Following the term "playbour," first coined by game researcher Julian Kücklich (2005), such platforms serve not only as laboratories for new human–technology relations, but also as playgrounds, in which humans and algorithms fuse into "playbouring cyborgs" (Dippel and Fizek 2017b).

Following sociologist Pierre Bourdieu's understanding of social space and different "social fields" (1985), play, science, and work can be understood as social fields each following their own specific logics. In the example of HC-based CS games, the "interferences" (Dippel and Fizek 2017a; 2019) of the different fields form a productive space in which HC systems unfold. This space, however, is not without friction as different field logics merge and, at times, conflict with one another. Transferring the term from physics, historian and cultural anthropologist Anne Dippel and media and game scholar Sonia Fizek use "interferences" to describe "the overlay" of work and play in the digital sphere and specifically in "[c]itizen science games as new modes of work/play in the digital age" (2019, 263). While Dippel and Fizek talk about "work/play" interferences in CS games, I focus on "science/play" interferences, which, of course, are a form of "work/play" interferences, because science is often understood as the counterpart (and sometimes even opposite) to play in my examples.

The science/play entanglements allow volunteer participants to engage in scientific projects in an enjoyable way, while (partly unresolvable) tensions and frictions also pervade the sociotechnical assemblages. By moving between these fields of everyday life, HC-based CS often uncovers unquestioned ascriptions of the entangled fields. Moreover,

14 The terms "citizen science" and "citizen scientists" remain controversial due to the meanings and exclusions they carry. For example, the term "citizen," according to the *Cambridge Academic Content Dictionary*, refers to "a person who was born in a particular country and has certain rights or has been given certain rights because of having lived there" (Cambridge University Press n.d.). Various alternatives have been proposed, such as *community science*, *participatory research* or *open science*, each including their own problems. For an overview of the different considerations, ongoing discussions, and alternatives, see, for example, Eitzel et al. (2017). Moreover, the mode of involvement of citizen scientists is much discussed in the CS literature. At its most simplified, while CS proponents claim that it makes science more democratic by opening up the production of knowledge to society, others understand CS as a "renewed approach to exploit citizens by making them work for free" (Vohland et al. 2021, 2), thereby criticizing CS projects for both reproducing hierarchies and exploiting volunteers without involving them in the actual knowledge production step (Vepřek 2021b). While I consider these questions throughout my research, they do not form the focus of my research interest. In this work, I use CS as a term from the field itself, choosing the term "participants" for "citizen scientists" (*cf.* Chapter 3).

the sociotechnical systems must not only be scientifically sound and technically functioning, but also engaging and enjoyable for participants. Considering *how* play and science interfere is crucial to understanding HC-based CS as assemblages and their continuously changing human–technology relations, since these interferences create specific affordances and open up new action potentials, which, if activated, can lead to new intraversions.

As I learned during my fieldwork, the scientific data analysis problem challenging the work of Alzheimer's disease researchers presented not only an interesting problem for the Human Computation Institute in Ithaca, NY to solve employing HC, but, at the same time, introduced productive constraints into the otherwise infinite space of possibilities (fieldnote Oct. 20, 2022). These constraints both facilitated building an HC system and set the direction for how the Human Computation Institute would build HC-based CS systems introducing "path dependencies," thereby guiding the further evolution of such systems and rendering some developments more likely than others (Klausner et al. 2015; De Munck 2022).

The project could build upon existing HC-based CS platforms, which, similar to the scientific constraints, introduced further path dependencies. However, the development of Stall Catchers—and HC-based CS systems more broadly—requires enormous effort in exploring the possibilities of human–technology relations, creating infrastructures, and developing algorithms. This is because the scientific problems tackled lie at the very frontiers of both AI and science.

The development of HC-based CS is shaped by visions of future human–technology relations alongside normative assumptions regarding how humans and machines *should* work together and how projects *should* unfold. More precisely, the envisioned human–technology relations of the future refer to participant–technology relations and questions regarding how to include unpaid and untrained volunteer participants in algorithmic systems and scientific research. Building upon the understanding that HC systems "all serve a purpose" (Michelucci 2013b, xxxvii), the Human Computation Institute considers it unethical to ask humans to perform a task that a computer can solve. This implies a necessity to evolve and adapt as soon as computational solutions advance and move on to new problems requiring human input. However, as I demonstrate in this work, such programmed inscriptions and a project's purpose and meaning by design are not uncontested. Instead, they are frequently challenged in their everyday unfolding by various human actors, such as participants and scientists, and materialities such as technical possibilities and breakdowns. Together, these continuously reshape the sociotechnical assemblage of HC-based CS projects.

Some participants of Stall Catchers, for example, objected to the project being labelled a game because that label did not properly reflect their motivation to contribute nor how they perceived their engagement.[15] They did not simply contribute to *just any* scientific research project, but had a personal connection to and were in a direct or indirect way affected by Alzheimer's disease. Participating in Stall Catchers, as I argue in Chapter 5, can be interpreted as a form of coping with everyday life marked

15 For this reason, I use the term "participants" throughout this work—rather than, for example, "players"— to refer to those who voluntarily engage in these projects as part of a crowd.

by this disease.[16] Analyzing participants' perspectives, their motivations to contribute to HC-based CS, and the meanings they ascribe to their engagement is important to understand how HC-based CS projects—initially imagined and designed by researchers and developers—are (re)negotiated in practice. These negotiations contribute to the formation of the assemblage and influence how human–technology relations in these systems unfold and intravert.

Thus, by considering not only the visions and design of HC-based CS, but also the motivations of the actors involved, "serendipitous discover[ies]" (Schaffer in Human Computation Institute 2018, 00:33), timing (Mousavi Baygi, Introna, and Hultin 2021), breakdown (e.g., Larkin 2008),[17] and the unruliness of nonhuman actors, it becomes possible to understand how the sociotechnical assemblage evolves. Moreover, and returning to the introductory example, it helps to analyze how, for example, the introduction of AI bots in Stall Catchers changes the participant–technology relations informing the calculation of "cyborg answers," as Michelucci described them (Human Computation Institute 2021, 22:25–22:26).

Human computation, and specifically HC-based CS as a research field and subject, has thus far primarily been addressed by computer science, information science, and related fields with a focus on quantitative and standardized analysis.[18] These studies do not centrally focus on the social, cultural or semiotic dimensions, which always represent a part of and form sociotechnical systems. As Barad aptly states, "[P]henomena are the place where matter and meaning meet" (1996, 185); I consider this to include the sociocultural sphere. However, HC systems do not merely imagine possible future combinations of humans and technology in order to move beyond today's AI capabilities and human abilities. As laboratories for such new combinations, they already impact, create, and change our everyday lives today. Moreover, given the rapid developments in the field of HC, which increasingly inform and contribute to AI discourse, it is important to analyze and critically engage with these developments. Through my research, I aim to contribute to a digital anthropological and science and technology studies (STS) understanding of HC and its human–technology relations. I also attempt to inform the development of HC systems by including perspectives from the various actors involved and considering their roles in forming the intraverting human–AI relations.

HC-based CS has thus far not been extensively analyzed in cultural and digital anthropological or STS investigations. However, important studies exist in these and related fields on crowdworking, CS, the relationship between play and work or science in the digital age. Such studies also extend to digital and media anthropology, the anthropology of technology or STS on human–technology relations and AI. I build upon and discuss these in Chapter 2.

16 I first discussed this idea at the conference "Breaking the Rules: Power, Participation, Transgression" of the International Society for Ethnology and Folklore in 2021 (Vepřek 2021b).

17 Like anthropologist Brian Larkin, I am interested in forms of everyday breakdown: "the small, ubiquitous experience of breakdown as a condition of technological existence" (2008, 234).

18 One of the few exceptions is the anthropologist Mary Gray and computer scientist Siddarth Suri's work on "ghost work" or crowdworking (2019), which I discuss in the related work section in Chapter 2.

In my research, I conducted inductive ethnographic fieldwork, drawing on praxiography (e.g., Knecht 2012) and grounded theory (Glaser and Strauss [1967] 1971; Charmaz 2000; 2014), over the course of three years (Oct. 2019 – Nov. 2022) in the US and Germany. To gain an in-depth understanding of how HC systems in the field of CS are developed and maintained, I joined the Human Computation Institute as an "intern" and worked together or co-laborated (Niewöhner 2016) with Michelucci and the institute's team. In the remainder of this chapter, I briefly introduce this field site for my research as well as the HC-based CS games I studied, and, finally, provide an outline of this book.

The Human Computation Institute refers to itself as an "innovation center" (Human Computation Institute, n.d.), and was initially founded as a Limited Liability Company in 2014 before reincorporating as a nonprofit in 2017. The first and most popular project of the institute, Stall Catchers forms the main example in my research, providing a suitable focus not only because it is a highly successful HC-based CS vis-à-vis participant engagement and "analytical throughput" (Michelucci, fieldnote Nov. 2, 2022), but also given the access to the institute I obtained. Stall Catchers was launched in October 2016, and currently (May 2024) has over 71,000 registered participants.[19] While most participants contribute during special events or only occasionally, the average number of monthly participants is 313;[20] the core, persistent and committed on a daily basis, consists of around 21 participants.[21] Stall Catchers can be accessed via a web browser or a mobile app and has been designed as a "casual" game that one can engage with for only a few minutes or over several hours. Contributions from Stall Catchers participants have also been recognized by referencing them as coauthors on scientific publications related to the project (Bracko et al. 2019; Ali et al. 2021).

I also draw from the analysis of two other HC-based CS games—Foldit and ARTigo—to contextualize Stall Catchers and its different perspectives more accurately and to gain a better understanding of elements that generally apply to HC-based CS. I briefly introduce these two comparative examples in what follows.

Foldit (Center for Game Science [University of Washington] et al., n.d.a) is one of the most long-term and successful CS projects utilizing HC. This online puzzle video game focuses on protein folding, in which participants are challenged to fold the structures of proteins as efficiently as possible.[22] Promising protein structures developed by partici-

19 I noted in my field diary on September 18, 2020, that the current number of registered participants was 29,314. By mid-2023, there were over 52,000 registered participants, meaning the number of participants had increased by nearly 80 percent over the course of my research.

20 I obtained the number of monthly participants from the Stall Catchers database using a SQL (structured query language) query. The query was run on March 27, 2023. This number reflects the search period, from October 1, 2016 to March 27, 2023.

21 I obtained the average number of daily participants from the Stall Catchers database using an SQL query, run on March 27, 2023. This number reflects the search period, from January 1, 2019 to December 31, 2022.

22 The 3D structure of proteins defines how they interact with other molecules and their biological function. Therefore, knowing how sequences of amino acids, the building blocks of proteins, fold into such a 3D structure is important in medicine (such as in developing drugs), biotechnology, and other scientific fields. Protein structure prediction attempts to infer a protein's structure from its amino acid sequence, taking into account the various forces determining a structure, such as hydrogen bonds. However, due to the many possible amino acid arrangements in space, predic-

pants together with algorithmic tools and automated scripts (and, more recently, with the assistance of the AI program AlphaFold) are tested in a wet lab. On their website, the Foldit team emphasizes the enormous contribution of human participants to research on diseases such as COVID-19, influenza, and even cancer and Alzheimer's (Center for Game Science [University of Washington] et al., n.d.c). Similar to the example of Stall Catchers, participants have been included as coauthors in scientific publications (Khatib et al. 2011).

Foldit is a collaborative project, specifically between the Center for Game Science and the Institute for Protein Design at the University of Washington in Seattle (USA) and other, mainly US–based research institutions.[23] Since its launch in 2008, more than 460,000 participants have contributed to Foldit, although the active player base consists of only a small fraction of these participants (Curtis 2015, 729). Foldit, as a "multiplayer online scientific discovery game" (Khatib et al. 2011, 18949) serves as an interesting example of HC-based CS, because it appeals to users in their creativity and spatial reasoning skills, as well as their skills in the development of 3D patterns. Thus, Foldit presents a rather different problem compared to Stall Catchers. Players—even those without prior biochemical knowledge—become highly qualified in the task by playing it extensively (*cf.* Khatib et al. 2011; Ponti et al. 2018), rendering Foldit particularly interesting for participants eager to learn and develop new skills. Compared to Stall Catchers, Foldit features a steep learning curve, causing some participants to drop out of the game early.

The field of protein structure prediction has significantly developed in recent years thanks to AI models such as DeepMind's AlphaFold and RoseTTAFold developed by the Institute for Protein Design at the University of Washington. Such developments have led to the declaration that the scientific problem of protein structure prediction is effectively solved (Moult in Callaway 2020). Foldit offers an intriguing example of the relations between AI and HC endeavors and how they influence each other, starting from the problem of protein structure prediction as a way to bridge the gap between what computers and AI can do and what humans alone can achieve. While first focusing on the problem of protein structure prediction, over time Foldit has shifted its focus to protein structure design, for which no fully automated solution currently exists. Just as Foldit's purpose has shifted over the years, the human–software and human–AI relations in the project are continuously intraverting, as I show in this book.

The third HC-based CS project I analyze is ARTigo (Ludwig-Maximilians-Universität n.d.a), a game platform developed at LMU Munich, Germany, resulting from a collaboration between the computer science and art history institutes. This project, similar to Stall Catchers, is also primarily related to AI problems within computer vision, but with a different twist: the tagging of digital representations of artworks. As an interdisciplinary

ting that structure remains a challenging task. Protein design, in contrast, describes the process of building new proteins that have specific functions or characteristics rather than modifying existing proteins. Both computational and experimental methods can be used.

23 The Cooper Lab at Northeastern University, the Khatib Lab at the University of Massachusetts–Dartmouth, the Siegel Lab at the University of California–Davis, the Meiler Lab at Vanderbilt University, and the Horowitz Lab at the University of Denver (Center for Game Science [University of Washington] et al., n.d.a).

project which began in 2007, ARTigo affords an interesting comparative example since it is both a long-term example of HC-based CS and a project *avant la lettre* in terms of its purpose and developments in the field of computer vision and deep neural networks. In 2017, ARTigo included a large database of more than 65,000 images of artworks (Bogner et al. 2017, 53). The integration of this large database into various GWAPs aimed to achieve two goals: first, to generate keywords for individual artworks facilitating a semantic search engine, and, second, to engage "lay art historians" (Kohle 2018, 1) by providing them with new learning opportunities while also potentially influencing established approaches to art history. By 2017, more than nine million annotations had been collected (Bry and Schefels 2016; Bogner et al. 2017, 53). However, after thriving in its initial years, ARTigo navigated a lean period, during which it was temporarily inaccessible or only accessible through the LMU network. This rendered the collection of empirical material difficult. Consequently, my analysis of ARTigo here is less detailed than that of Stall Catchers and Foldit, primarily featuring a subsection of Chapter 6 only. Nonetheless, the project regained momentum in November 2022,[24] when relaunching on a new platform, featuring new games and addressing new image recognition issues. ARTigo's relaunch and the evolution of its human–technology relations accompanying the new computational possibilities and advancements can also be understood through the concept of intraversions.

This book spans eight chapters of which Chapters 4 through 7 present the core analysis of my research. Chapters 2 and 3 lay the groundwork for the empirical chapters. More specifically, in Chapter 2, I discuss the related literature from cultural and digital anthropology, STS, and related fields, and the theoretical perspectives I build upon in my analysis, drawing specifically from assemblage theory and thinking, relational conceptualizations of technology and human–technology relations, moral anthropology, and the ethics of technology. Moreover, building upon cognitive anthropologist Edwin Hutchins (1995b; 1995a) and Barad (1996), I develop and discuss the concept of intraversions. In Chapter 3, I present and discuss the methodological approach, based on co-laborative ethnographic fieldwork combining classic ethnographic methods such as participant observation, qualitative interviews, and media analysis with the more experimental analysis of code, the Stall Catchers in-game chat, and collaboration with the Human Computation Institute. I consider my own role in the development of HC-based CS, which I ultimately revisit in the conclusions to the book to discuss how cultural anthropology can contribute to the development of (hybrid)[25] sociotechnical AI systems.

The first empirical chapter (Chapter 4) then focuses on the visions, imaginaries, and designs of advocates, designers, and developers of such HC-based CS systems in the context of HC research. Here, I explore how they are imagined as counternarratives to strong AI, while sharing much in common, and what visions of human–technology relations in the future underlie the design of these ethical projects. The fact that they are designed

24 Information was kindly provided by the ARTigo team via an email exchange (Mar. 26, 2023).

25 In the following, "hybrid" can refer to both a term used in the fields of HC and HI, or one used by STS and feminist researchers and in the philosophy of technology. Wherever I refer to it or use the term, it should be clear from the context to which field or scientific tradition the term refers.

as open systems that can be understood as in-betweens on the way to developing HI is crucial to the possibilities of human–technology relations intraverting. Since imaginaries and visions must materialize to drive the development of HC, the second part of this chapter analyzes examples of infrastructuring (Bossen and Markussen 2010; Niewöhner 2015) performed at the Human Computation Institute.

This perspective, which focuses on design and initial implementation, is not only informed by directions and visions, but just as much by everyday negotiations. I turn to these in the next chapters. Chapter 5 discusses how these inscriptions of visions, values, and norms are continuously contested and negotiated in everyday life through various motivations, interests, and aims. Such inscriptions drive, for example, CS participants and the software's affordances (Gibson 1977; 1979; Bareither 2020a), materialities, and action potentials emerging from human–technology relations, all of which are situated in the entanglements of play and science. I focus here on discussing the multiple meanings of the case studies. To do so, I employ the example of how participants challenge the designer's image of them, adapt systems in their own ways, and ascribe different meanings to them than those intended by design. My analysis illustrates how these projects are included in the participants' everyday lives, which, for example, for some, are marked by a deadly disease. In the second part of Chapter 5, I turn to the interferences of play and science, which, on the one hand, productively create a seamless space, while, on the other hand, create tensions and frictions, together forming the assemblage. Within these entanglements, human–technology relations in HC-based CS unfold and continuously change.

While Chapters 4 and 5 provide a fundamental understanding of the formation of HC-based CS assemblages, in Chapter 6 I further build upon this analysis, investigating examples of human–technology relations in the HC-based CS games in detail and how they continuously intravert over time. Using the concept of intraversions, I demonstrate how tasks are redistributed, how practices change, and how role allocations shift alongside intraversions. First, the focus lies on participant–technology relations in Stall Catchers and Foldit and how they evolve in daily life and over time through the meshing of HC visions and everyday negotiations, the multiplicities of meaning of HC systems, and within the space created by the play/science entanglements. HC-based CS projects not only consist of sociomaterial participant–technology relations, despite the HC literature commonly only referencing participants when it talks about "humans in the loop." With the aim of developing a better understanding of the different actors and relations forming HC systems in CS as sociotechnical assemblages, I move to the human–technology relations developers and researchers of HC-based CS projects enter into, using the example of researcher–technology relations in Stall Catchers. Just as participant–technology relations intravert over time, researcher–technology relations are never fixed, but evolve alongside the introduction of new tools or automated steps in the data infrastructure connecting the biomedical engineering laboratory to the CS gaming platform. This infrastructure is never complete, requiring continuous work and improvements. My analysis of human–technology relations employing the concept of intraversions brings forth a pattern, which, by turning away from the microanalytical perspective of HC systems in their everyday situatedness, also allows for a better understanding of the nontrivial and dynamic relations between HC and AI research. Finally, at the end of this chapter, I demonstrate how the concept of intraversions can be applied in a fruitful way to describe the evolution of HC-based CS in relation to AI advancements using the example of ARTigo.

In the continuous formation of the HC-based assemblages, intraversions destabilize established practices, requiring different processes of alignment. Chapter 7 then focuses on trust as an example of such alignment processes and how it is built in and with HC. Trust, as I understand it in this chapter, is not a mere cognitive phenomenon, but unfolds in sociomaterial practices and within human–technology relations. It plays a constitutive role in assemblages and needs to be adjusted and reestablished with intraverting relations. In this chapter, I, thus, analyze trust in HC-based CS collaborations, how it is programmed algorithmically, and the role it plays from the perspective of participants.

In this book's conclusions, I bring together the various perspectives and scales of analysis, arguing that cultural anthropological and STS research can help us understand HC systems and the hybrid modes of becoming of their human–technology relations. Inspired by STS anthropologist Lucy Suchman (2007b; 2021) and cultural and feminist anthropologist and early STS researcher Diana Forsythe's (2001f) fieldwork, my study also illustrates the value of ethnographic research in HC development. Here, I emphasize the need for HC development to consider all actors and human–technology relations involved. It should integrate various aspects of everyday life, as well as the relations' historical evolution, path dependencies, and existing relations remaining from the past, and understand and make explicit its underlying future imaginations and visions.