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Mapping Citizen Science through the Lens of Human-Centered AI

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ABSTRACT

Artificial Intelligence (AI) can augment and sometimes even replace human cognition, but still has many fundamental roadblocks preventing it from achieving fully autonomous applications. Inspired by the growing set of AI-implementation failures in society at large, in this opinion piece we reexamine the field of Citizen Science (CitSci) through a computational lens, highlighting algorithmic opportunities as well as uniquely human capabilities. In particular, we situate the CitSci field among human and machine computation fields and introduce two novel dimensions allowing us to match CitSci projects ranging from digital games and annotation tasks to data collection in nature to the appropriate machine learning algorithms. Interestingly, in CitSci there is an abundance of tasks drawing upon human common sense, hierarchical thinking, and complex skills which have yet to be incorporated in current AI methods. This gap, combined with the unique participant-centered set of values, makes CitSci an invaluable test bed for the development of human-centered AI of the 21st century such as hybrid intelligence. The mapping thus offers concrete algorithm selection guides to CitSci researchers as well as inspiration for AI researchers to pursue grand AI challenges through support of CitSci projects.

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1. INTRODUCTION

This opinion piece is conceived in response to the critical question which Franzen et al. (2021) articulate well: with increasingly powerful AI, what is the human's role in Citizen Science (CitSci)? AI certainly has its place in taking over boring, labor intensive aspects of work, speeding up analysis, and optimally distributing tasks to humans (Lotfian, Ingens and and Brovelli, 2021); however, we argue strongly against the position that AI can or should completely take over all once human-dominated CitSci tasks.

CitSci projects enhance scientific research by tapping into the collective cognitive and labor resources of the general public. Indeed CitSci attracts hundreds of thousands of participants to research projects that utilize human problem-solving for tasks of varying complexity. Researchers use CitSci when they are unable to collect the necessary data by themselves (Wyler et al., 2016), need specific expertise from the general public to help solve a problem (Danielsen et al., 2018), datasets are too large or complicated for the researchers to process with their own technology and resources (Das et al., 2019; Fortson et al., 2011; Nugent, 2019), or the degrees of freedom of a system results in nearly infinite possible candidate solutions to be explored (Jensen et al., 2021; Koepnick et al., 2019).

To a large extent, the growth in scale and complexity of contemporary CitSci projects has been attained by digitizing social interaction, communication, and access to projects. With these initial steps of digitization of the connectivity, the CitSci field seems poised to also substantially involve computers in problem-solving by building efficient, sustainable, human-computer partnerships.

In recent years, Machine Learning (ML) applications (a sub-field of AI)[1] have become increasingly widespread making it possible for researchers to work with larger amounts of data or detect patterns that would be hidden to the human eye (Eager et al., 2020; Li et al., 2017; Silver et al., 2016). Following this global trend, the integration of ML into CitSci projects is on the rise. Specific CitSci tasks using the sub-class of ML, supervised learning (SL) for the classification of ecology images are most commonly reported on (Picek et al., 2022; Willi et al., 2018). Neural networks are also used for RNA puzzle solving (Koodli et al., 2019) as well as with respect to broader engagement and retention of CitSci volunteers (Zaken et al., 2021). Following these early attempts of ML adoption in CitSci, there have been several recent meta-analysis articles discussing various risks and opportunities for ML in CitSci (Cecerroni et al., 2019; Franzen et al., 2021; Lotfian et al., 2021). These articles focus almost exclusively on applications of and ethical concerns brought on by SL used for classification tasks. Given the abundance of ML techniques beyond just SL such as reinforcement and unsupervised learning, there seems to be a gap in current CitSci literature concerning the broader potential of implementing AI to both assist existing CitSci applications and help developing entirely new solutions.

In this opinion piece we argue that examining CitSci projects from the viewpoint of quantifying the human cognitive and/or motoric effort needed to make a scientific contribution could yield valuable insights around potential human-computer processes that could be served by human common sense, structured learning, and real-world experience. This human-centered, computational lens allows us to define a novel spectrum of degree of task digitization spanning CitSci games, annotation tasks and physically based environmental monitoring. We then match the characteristics of each of these types of CitSci tasks to distinct forms of AI. Herein, we provide implementation advice for CitSci and AI practitioners and contend that CitSci contains certain characteristics (detailed below) that will uniquely enable the field to contribute to some

[1] For a visual overview on the differences between ML and AI see Lotfian et al. (2021) pg. 3

of the outstanding grand challenges facing human-centered models of AI in the 21st century.

1.1 Pitfalls of current AI and a case for Hybrid Intelligence in Citizen Science

The widely publicized success of ML based applications in recent years has given rise to a misplaced techno-optimistic belief that purely autonomous AI problem solutions are imminent. However, there is a growing recognition that autonomous deep learning-based approaches often are not robust enough to solve real-world problems in noisy, unpredictable and dynamically varying environments including serious failures in visual recognition, chatbot training, and self-driving cars (Heaven, 2019; Marcus, 2018). Many tasks can therefore still only achieve the required quality and reliability with some form of human-in-the-loop input for training, execution or verification (Benedikt et al., 2020; Zanzotto, 2019). Even highly publicized research on self-learning AI in games such as AlphaZero has either required manual adaptation (Silver et al., 2018) or extensive learning from human data (Vinyals et al., 2019) and has been exceedingly difficult to generalize beyond its field (Dalgaard et al., 2020; Tomašev et al., 2020).

Although AI methodologies are applied in many CitSci projects, little attention has been given to the growing body of research on bi-directional, mutually beneficial, human-computer interaction (Schmidt et al., 2021). Well designed, human-centered AI solutions augment humans by bringing them more intimately into-the-loop (Christiano et al., 2017; Dellermann et al., 2019; Michelucci and Dickinson, 2016; Schneiderman, 2020). Initial steps in this direction include capturing failures of the stand-alone AI system by querying humans for feedback about a certain selection of predictions made by an algorithm (Kamar and Manikonda, 2017; Nushi et al., 2018). The concept of Hybrid Intelligence (HI), a sub-class of human-centered AI, has been rather loosely defined in previous literature (Akata et al., 2020; Lasecki, 2019; Prakash and Mathewson, 2020). In our work we operationalize HI in terms of three criteria put forward by Dellermann et al. (2019). 1. Collectiveness: the human and AI are solving the task collectively towards a system-level goal. Sub-goals of individual agents might be different from the system-level goal; 2. solution superiority: the sociotechnical system achieves results superior to that one of the individual agents (human or AI); 3. mutual learning: the system improves over time, both as a whole and also each single component (human and AI). Although it is not the aim of this opinion piece to provide concrete development guidelines, we do believe that the criterion of mutual learning will provide inspiration to CitSci researchers to consider how to ensure that their citizen scientists learn how the AI "thinks" as well as to AI researchers to consider how to ensure that their algorithms adapt to the preferences and working styles of the individual users in order to pursue maximally synergetic human-AI interfaces.

We argue that the field of CitSci is well-suited for developing integrated human-machine interactions for two distinct reasons. First, although many fields of science involve human problem-solving, the human computation being performed in science in general is often defined implicitly through the tacit domain-specific experience of the involved experts. In contrast, CitSci specializes in explicitly transforming conventional research challenges into tasks adapted to the problem-solving abilities and collective intelligence of the general public. Thus, we argue that CitSci provides a unique snapshot of the current human-machine problem solving boundary because CitSci projects remain active only as long as the core challenge is unachievable by other (computational) means. Second, the long-term value of hybrid interactions may not always be immediately apparent because developing interfaces to optimally support human creativity is challenging. Therefore, commercial applications may tend to focus more narrowly on short-term efficiency maximization using shallower, but predictable human involvement (Rafner et al., 2022). In contrast, CitSci is fueled by a desire to solve concrete tasks and to generate intrinsic value for participants, a motivation at the heart of the growing and closely related field of AI for social good (Bondi et al., 2021; Hsu et al., 2022). We argue that the combination of these practical and value-based considerations make CitSci particularly well-suited to develop hybrid intelligence into concrete projects. These in turn, can benefit AI as a field as well as bringing value to CitSci projects, their participants, and science and society at large.

Based on extensive discussions between the 17 co-authors and iterative mapping exercises analyzing a handful of CitSci projects through the lens of HI we:

i. Provide a conceptual mapping of fields and terms computationally related to CitSci to promote knowledge exchange from each research tradition towards optimal human-machine problem-solving.
ii. Argue that two new, underexplored dimensions emerged during this analysis: the degree of task digitization and the accessibility to make a scientific contribution.
iii. Apply this classification scheme to a selection of projects to (a) illustrate which types of CitSci tasks are best suited for which types of machine support and (b) highlight the importance of more deeply understanding the cognitive skills and training necessary to complete CitSci tasks.
iv. Present a list of open challenges for human-centered AI in the field of citizen science.

2. WHAT TERMS MATTER AND WHY: TYPES OF COMPUTATION, EMERGENT INTELLIGENCE AND CITIZEN SCIENCE

Before reexamining CitSci through the lens of HI it is important to clarify the relation of these two fields to related areas such as human and machine computation and collective intelligence and crowdsourcing. While the relationships between some of these fields has been studied extensively (Lease and Alson, 2018; Suran et al., 2020) we disagreed with previously suggested overlaps of fields (Dellerman et al., 2019; Newman, 2014; Quinn and Bederson, 2011) and found there were no previously established diagrams which provide the comprehensive overview needed for positioning our discussion. For example, Newman (2014) leaves a part of crowdsourcing outside of collective intelligence. We disagree with this as all forms of crowdsourcing involve multiple agents and all outputs of crowdsourcing that we are aware of would fit into the inclusive definition of collective intelligence as intelligence that emerges from the collaboration and competition of many individuals (Lévy & Bononno, 1997; Russell, 1995). Dellermann et al. (2019) demonstrates a rather generic relationship between human and artificial intelligence and does not allow for machine-only collective intelligence although this domain forms a rapidly growing branch of computer science (Jangra, Awasthi, and Bhatia, 2013. Thus, through an iterative mapping exercise between all 17 co-authors we combined and improved on the three previously published mappings (Dellerman et al., 2019; Newman, 2014; Quinn and Bederson, 2011). For a full list of terms we reviewed when arriving at our figure, see supplemental File 5.

Here, we map the concepts based on the axes of types of computation (biological, human, and machine) and number of agents. Each axis has an emergent intelligence (Bonabeau et al., 1999) associated with it: hybrid intelligence and collective intelligence respectively. We provide a diagram illustrating the relationship between central fields (Fig. 1) followed by a table on the terms used (Table 1).

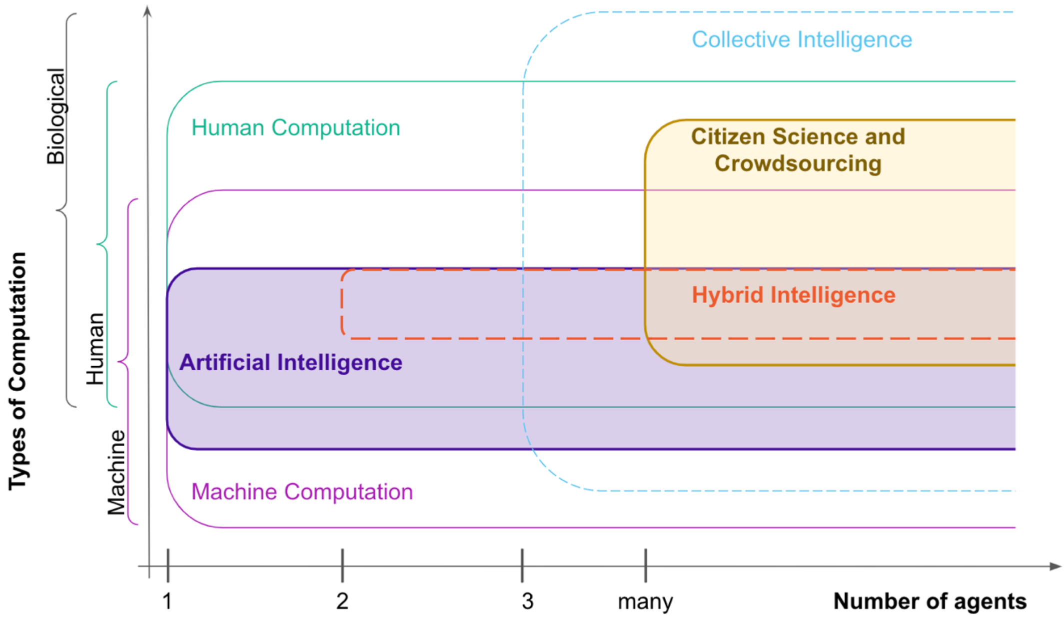


Figure 1. ***The diagram illustrates the relationship of Artificial Intelligence and Citizen Science in the reference frame of mixed-agent computation (y-axis), moving from machine to human and finally to general biological computation, and agent (biological individuals or machines) count (x-axis) moving from one agent to many.***

Computation
General information processing

Biological computation (Mitchell, 2011)
- A form of computation
- Performed by living organisms
- parallel, stochastic, with no clean notion of a mapping between "inputs" and "outputs"

Human computation (Michelucci, 2013)
- A form of biological computation
- Performed by an individual human, groups of humans, and can be mediated by machines
- Human intelligence is always used as humans are assumed to always act with 'intelligence'

Machine computation (Copeland, 1997)
- Information processing through clearly defined rules (algorithms), done by machines/computers which may not always be 'intelligent' but also includes AI

Emergent Intelligence
Emerges when multiple agents (human or machine) collaborate on a common goal

Collective Intelligence (Lévy & Bononno, 1997; Russell, 1995)
- Associated with collaboration or competition of **many** individual agents (human ***AND/OR*** machine)
- Emerges with 3 or more agents (Woolly et al., 2010)

Hybrid Intelligence (Dellermann et al., 2019)
- Arises in systems combining human agents ***AND*** AI
- Superior results are achieved than either the human or machine could have accomplished separately
- Both the human(s) and AI(s) continuously improve by learning from each other

Artificial Intelligence
Form of machine computation applied to tasks that have traditionally required human intelligence (Bellman, 1978)

Machine Learning (ML) overview
- Suite of methods used in AI
- Based on algorithms whose function is not fully determined by a program but rather acquired via a learning session called ***training***
- Example input-output data pairs presented to the algorithm while parameters (collectively called ***'the model'***) of the algorithm are empirically adjusted so that the input produces the desired output
- Once the model is trained, parameters are fixed and the algorithm can be ***executed*** on novel inputs to provide predictions or decisions

ML type 1: Supervised learning
- ***Objective***: predicting a specific class label classification) or a parameter value (regression) for any given input
- ***Training*** contains ground truth labels assigned to a set of individual input examples which is usually obtained by human labelling or resulting from experimentation or simulation

ML type 2: Unsupervised learning
- ***Objective***: classify input samples without knowledge of class labels using a measure of similarity, typically calculated as distances in many dimensional space
- Includes dimensionality reduction where prominent features or representations are extracted based on their ability to to distinguish the input samples

ML type 3: Reinforcement learning
- ***Objective***: optimize behavior of an AI agent which reacts often repeatedly, to the state of the environment
- Agent received feedback on its action from a reward function
- The environment can be real (as in robotics), a closed digital model like a game world, or a simulation of some process

Table 1. ***Overview of types of computation, emergent intelligence, and artificial intelligence that are referred to throughout the paper.***

HI is a subset of the overlap between Human Computation and AI. As HI can be achieved with only two agents, it lies partially outside of Collective Intelligence which requires at least three agents. HI necessitates at least one human and one AI whereas there are forms of both non-biological (Camazine and Sneyd, 1991; Bonabeau, 2002; Reid and Latty, 2016) and only artificial collective intelligence (Jangra, Awasthi, and Bhatia, 2013). Apart from collectiveness and solution superiority, HI poses a rather strict requirement of mutual learning, which explains the substantial overlap between CitSci and AI as well as an overlap of AI and Human Computation beyond the area of HI. Since few projects today achieve all three HI requirements, the size of the HI field on Fig 1 is overrepresented. However, HI's importance will likely accelerate as algorithmic development increasingly focuses on human-centered AI (Auernhammer, 2020; Schmidt, 2020; Shneiderman, 2020).

3. TWO NEW DIMENSIONS FOR EXPLORING CITIZEN SCIENCE PROJECTS

We now discuss our two novel axes for determining which CitSci tasks are ideally suited for which types of machine support. As demonstrated below, the first axis, degree of task digitization, allows for a rough categorization in terms of the potentially applicable forms of AI, it does not explain why some tasks within each category are easy for most participants and some can only be solved by a minority. To address this question, we propose the term, accessibility to contribution, which we define as: "the likelihood that an average layperson (assuming there are no exclusionary factors to participation, e.g., physical, socio-cultural, financial, or technological) would make a scientific contribution to the particular project." This category can be considered a cognitive axis and is a pragmatic aggregation of a number of cognitive and interaction design factors such as the level of expertise/experience and effort required, the level of task support as well as the character of the scientific evidence to be gathered (see below for concrete examples). Note, even though a task may routinely be solved by participants, it should not be taken as a sign of computational simplicity, since tasks easily completed by humans (e.g., related to human common sense) can be quite challenging for AI. We hope that this CitSci task mapping may lead to increased appreciation of the multitude of human-processing going on in CitSci projects that are still far from being automatable in any foreseeable future.

We conducted a literature mapping exercise between all 17 co-authors, mapping 19 projects onto these axes (Fig. 2) based on their knowledge of the projects. This reflects our expert opinions on the placement of the projects. We call for future studies to empirically investigate our proposal, particularly, the cognitive dimensions involved in delineating the axis of contribution.

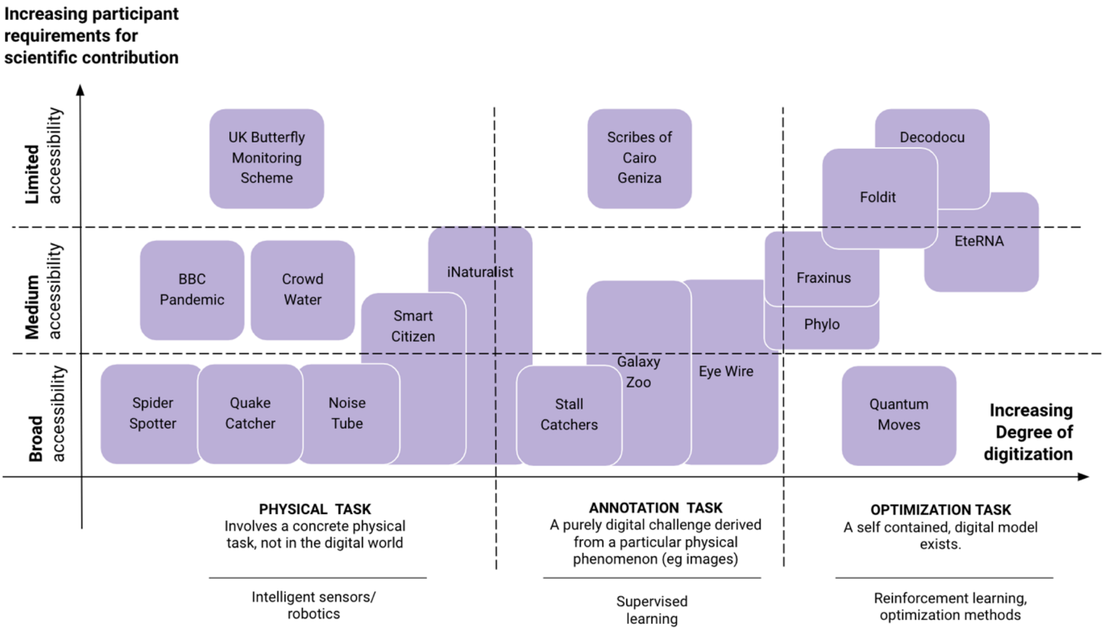


Figure 2. ***Mapping of Citizen Science projects. The x-axis shows an increasing degree of task digitization moving from physical tasks (potentially supported by robotics and smart sensors), through annotation tasks (potentially supported by supervised learning methods) to purely mathematical, optimization tasks (potentially supported by reinforcement learning methods). The y-axis represents accessibility to scientific contribution with highly accessible projects at the bottom and projects with extensive requirements on special cognitive traits, expert knowledge, or training at the top. Projects that span multiple categories on either the X or Y axis have tasks which fall into different categories.***

3.1 Digitization degree of the CS tasks

We propose a granular description and classification of projects based on three different categories of task digitization: physical tasks, annotation tasks, and optimization tasks.

Note that in this work we include only projects in which the participants are epistemic subjects (rather than objects), meaning that they actively gather external knowledge and are not the objects of study themselves (Kasperowski and Hilman 2018). This means that the field of citizen psych science is excluded (Coughlan et al., 2018, Jennett et al., 2014, Pedersen et al., 2020). In the same vein we exclude projects in which the knowledge generation challenge is identical to the scientific discipline. Thus, classification of birds and written documents is included if the scholars are biologists and historians but excluded if the scholars are computer scientists only interested in training their algorithms. Lastly, we exclude ML applications in CitSci projects which deal with content and task distribution and recommendation systems (Zaken et al., 2021) as these systems can be applied across all three categories of task digitization.

Physical Tasks require participants to perform non-digital, motoric actions, to acquire data such as birdwatching. In these tasks, the participant needs to continually (audio-visually) survey the environment and/or consider the suitability of deploying a sensor for recording data (Camprodon et al., 2019; Cochran et al., 2009; D'Hondt, Stevens and Jacobs, 2013; Van Horn et al., 2018). The machine analogy of the data collection task would be robotics and smart sensors. In smart sensors, the raw measurement data is processed locally in the hardware before being passed to a central data storage for further processing (Cartwright et al. 2019, Kim et al. 2010). Advanced robotics would include adaptable sensors which adapt (e.g. move location) independently. Note that even the deployment of a stationary sensor includes complex cognitive and socio-technical considerations such as evaluation of the environment in terms of e.g. degradation of the sensor or risk of theft.

Annotation tasks of previously acquired data are mostly solved via a digital platform, but require subject-specific or disciplinary knowledge, even if at a layperson level. Thus, one cannot score the participants' input objectively. Instead, the annotation is consensus-based (absence of a ground truth). The elements to be annotated are often images or audio recordings or transcriptions (Causer and Terras, 2014; Lintott et al., 2008; Nugent, 2019; Tinati et al., 2017). The annotated data can be used to train ML classification models which fall into the paradigm of supervised learning (SL). Franzen et al. (2021) refers to a subset of these types of tasks as 'classification,' however this term is not broad enough to encompass transcription analysis which is analyzed using the same ML paradigm and thus fits under the umbrella category, annotation tasks.

Optimization tasks involve completely digital data acquisition and analysis within systems which can be described with a self-contained mathematical model such as with in physics (Jensen et al., 2021; Wooton, 2017), mathematics (Rafner et al., 2021) and biochemistry (Curtis 2015; Lee et al., 2014). By self-contained model, we mean a task that can be unambiguously and automatically evaluated (scored) in terms of how well a candidate solution solves the problem without any further human input. These are problems that can often—in theory—be solved purely by machine computation, but in practice may become intractable due to high complexity of the solution space. Naturally, these tasks lend themselves well to ML methods related to optimization in complex spaces, such as reinforcement learning (RL).

The **degree of task digitization** allows for a rough categorization of the possible AI-contribution as robotics/smart sensors, SL, or RL respectively. One might naively expect that the pinnacle of human contribution is to solve complex mathematical problems (high degree of digitization tasks). However, in many ways the robotics/ smart sensors capable of assisting or replacing human volunteers in the real world for physical tasks is a much more difficult problem, considering current robotics are comparably less advanced than the state-of-the-art RL technologies (Dalgaard et al., 2020, Vinyals et al., 2019). This clearly demonstrates that the degree of digitization should not be mistaken for an axis of increasing cognitive complexity. We therefore posit that: a systematic comparison of CitSci tasks and relevant modern computational capabilities will lead to increased understanding and appreciation of the multitudes of tasks that human volunteers perform, and how that labor works alongside technology and ML.

The x-axis of Figure 2 plots projects according to the degree of task digitization. As illustrated, there may be projects exhibiting a mixture of features from two categories. Another boundary case is CitSci remote optimization of concrete experiments (Heck et al., 2018), which would clearly be amenable to RL treatment but requires execution of a real-world experiment in order to evaluate the quality of any given user-specified candidate solution and therefore does not have a self-contained model. Another example is the CitSci game EteRNA where participants create RNA designs which can be partially evaluated within the software but must then be synthesized through a remote wet laboratory experimental pipeline to assess design candidates (Lee et al., 2014). Finally, we note that the ML technique of Unsupervised Learning is absent here because it is a data analysis technique that can in principle be applied to any data set across the categories. In the following we illustrate the relevance of these task characteristics through several specific CitSci projects (see appendix A for all considered projects).

3.2 Digitization degree of the CS tasks

To elaborate on the **accessibility to contribution** axis, we present nine examples, a subset of CitSci projects reviewed, and discuss what it takes for a participant to make a scientific contribution. We propose a spectrum along which projects can be ordered to signify broader or more limited accessibility to contribution. We note that this framework has already found applications in the field within recent considerations of barriers to expertise in CitSci games (Miller and Cooper, 2022).

To help operationalize the proposed two axes, we provide a table of concrete examples. Please note, the projects explained below were chosen based on the extensive firsthand knowledge from the 17 co-authors and are not an exhaustive list of citizen science projects that could be categorized.

Optimization tasks

Quantum Moves 2 is a real-time dynamics control game designed to tap into a player's *intuition* of water sloshing in a glass as they move an atom through a 2-dimensional space over the span of a few seconds. Apart from investigating the value of each individual human input, there is an emphasis on understanding the aggregated collective input to gain understanding of the generic intuition-driven strategies (Jensen et al., 2021). The data analysis in Quantum Moves 2 builds on a bulk analysis of all player data and thus these heuristics are gleaned from all player data submitted after the completion of the short tutorial. *broad accessibility*
Foldit is a puzzle-type game designed to visualize proteins in three dimensions, and lets participants spend as long as they need, while the puzzle is available, to slowly and (semi-) systematically search through a complex parameter landscape as they attempt to find the best folding pattern for a specific protein (Cooper et al., 2010). Reported results focus on the small subset of participants that arrive at uniquely useful solutions (Eiben et al., 2012; Khatib et al., 2011). *medium-limited accessibility*
Decodoku is designed for participants to solve sudoku-like quantum computing challenges without a time limit (Wootton, 2017). Data are only collected in the form of written reports emailed to the scientists where participants not only have to come up with useful strategies but also be able to reflect on and verbalize their strategies. *limited accessibility*

Annotation tasks

Stall Catchers is designed to facilitate analysis of data related to Alzheimer's research. Participants are presented with few-second video clips of blood vessels from the brain of mice affected with Alzheimer's. Through analyzing the movement of blood cells in a target area determined by the game, they classify images as either flowing or stalled, and mark the precise location of stalls on the images. The puzzles require non-domain specific skills and can be solved with minimal domain knowledge (Nugent 2019). *broad accessibility*
In **Galaxy Zoo** participants classify images of galaxies according to a series of questions (Lintott et al., 2008). Some questions are approachable with minimal domain knowledge (e.g., "Does this galaxy have spiral arms?") while others benefit from experience (e.g., "Is there anything odd?"). Examples and illustrative icons help teach new participants how to participate. *medium-broad accessibility*
Scribes of Cairo Geniza is a transcription project, where participants are presented with images of historic text fragments in Hebrew and Arabic and transcribe it one line at a time using an online program. Participation requires specialized training and/or prior knowledge when dealing with specialized objects due to language requirements (Scribes of the Cairo Geniza n.d.). *limited accessibility*

Physical Tasks

Quake-Catcher Network is a real-time motion sensing network of computers for earthquake monitoring. Participants download the software and purchase a USB sensor device, which records seismological waves while the software algorithmically determines waves outside the normal range, and sends them back to the project server. Participation, apart from the initial setup, does not require active action or skills of the participant (Cochran et al., 2009). *broad accessibility*
iNaturalist is an online social network, where participants can share biodiversity information by recording observations of organisms or their traces (nests, tracks etc.). Users can add identifications to these observations and an automated species identification algorithm is also used on the platform. Participation requires none to extensive domain-specific skills, depending on whether the user wants to also perform identification tasks. Observations can be used to monitor organisms at various locations

(iNaturalist, 2021). *broad-medium accessibility*
UK Butterfly Monitoring Scheme (UKBMS) is a recording protocol used to record data on the butterfly population. Participants walk 1-2 km routes weekly at specific times of the day, in specific weather conditions from spring to fall multiple years in a row. The task is to record measurements on e.g., weather, habitat, and the number of different butterfly species on recording forms which are submitted weekly on the project website. Significant time investment, prior domain knowledge, and detailed environmental surveying skills are required; participation is limited to the United Kingdom (Dennis et al., 2017). *limited accessibility*

As we see, accessibility to contribution is determined by requirements such as: expertise through training (e.g., animal identification skills), experience (becoming familiar with the task environment and interface, e.g., Foldit), and certain cognitive skills (currently understudied in CitSci). Although at this point these factors are difficult to assess, if they are properly understood, AI can be used to broaden accessibility by automatically adapting to the diverse needs and skills of participants, facilitating quality of contributions (Anderson-Lee et al., 2016; Walmsley et al., 2020) and making the task simpler and more enjoyable for participants (Kawrykow et al., 2012). Attempts have been made to optimize the interactions between the volunteers and the scientific tasks of the CitSci project increasing engagement and optimizing quality of contributions (Sterling, 2013). However, without an appropriate underlying framework the experiences from these specific examples are difficult to transfer to other projects. As an initial step in this direction, Von Rueden et al.'s taxonomy of informed machine learning provides an interesting and potentially helpful organization of types of prior knowledge (e.g. scientific knowledge, world knowledge or expert knowledge), the representation of the knowledge and how it is integrated into the machine learning pipeline (von Rueden et al., 2021).

While an in-depth analysis is beyond the scope of this opinion piece, we argue that our initial categorization allows for joint considerations about cognitive and learning processes of participants as well as possible computational models of AI applicable across a wide range of CitSci projects. In particular, we demonstrate that across CitSci projects there exists a class of tasks that is characterized by intuitive processing and the application of common sense (information processing or physical actions that most participants can do almost instinctively). In these cases, nearly all participants can contribute to using general human cognitive and motoric abilities (see Fig 1, y-axis) thus have "broad accessibility". The apparent simplicity of these tasks from the human perspective stands in dramatic contrast to the challenge of replicating them with AI technologies, which is one of the grand challenges of the AI field (Marcus, 2018, 2020). At the other end of this spectrum lie projects where only a small fraction of participants are able to contribute (e.g. Decodocu, UK butterfly monitoring scheme), thus have "limited accessibility". Here, understanding of how task learning can be combined with systematic exploration and intuitive leaps remains another grand challenge of AI. Interestingly, most limited accessibility tasks also draw heavily on many skills such as creativity and complex problem solving, which still elude a firm theoretical understanding in the fields of psychology and education. Nevertheless, a further analysis of the particular cognitive processes going on in CitSci projects will be crucial for designing future automated support systems to enhance the contribution of the participants.

Finally, the meta-cognitive aspects in the Decodoku example illustrates that it would be interesting to relate the accessibility level to the emerging concept of co-created CitSci (Bonney et al., 2009b), in which participants are involved not just in the data gathering phase of the scientific process but also e.g. hypothesis generation, design, and analysis (Hidalgo et al., 2021). The algorithmic support of the scientific processes beyond data acquisition could seek inspiration within cutting edge AI trends such as unsupervised ML, hierarchical modeling (Menon et al., 2017) and generative design (McKnight, 2017; Oh et al., 2019).

4. CONCLUSIONS AND OUTLOOK

As mentioned above, this opinion piece is a strong argument against the position that AI can or should completely take over all once human-dominated CitSci tasks. In addition to making room for participants to contribute to multiple aspects of the research cycle we can use AI as a lens to reflect on and ultimately more deeply understand human skills such as hierarchical thinking, problem solving, and creativity which are current roadblocks in state of the art AI such as (Jensen et al., 2021, Marcus, 2018). Using AI in the reflection process to understand more about human cognition and problem solving is already well underway in interdisciplinary domains such as computational co-creativity (Feldman, 2017), but under-investigated in CitSci projects.

As outlined in the introduction, a key quality of HI as defined by Dellermann et al. (2019) is that mutual learning exists among the AI and human components of the system. Such integration not only allows for, but necessitates the co-evolution of individual components (AI and human alike) with each other and the systems to which they contribute. Thus, we are entering into uncharted AI territory, where our best hope for advancing the field may require bootstrapping. In other words, the potential complexity of these systems suggests an opportunity to use HI itself to improve our understanding of HI. Asking why a given CitSci project is not solved entirely algorithmically can be a path to identifying new modes of human-machine problem solving by discovering suitable existing machine technologies and as well as to deeper appreciation of the distinctly human contribution in areas where current machine technology falls short.

Importantly, the three HI criteria provide a philosophical and operational framework for enriching the human role in a system (Rafner et al., 2022), rather than human-in-the-loop ML methods designed to move towards pure automation of CitSci tasks (Picek et al., 2021). Following this opinion piece, initial studies have looked at optimizing the AI-human workflow in CitSci (Gal et al., 2022), but considerable more research is needed in this area. Concretely HI holds the potential to be used as a tool to augment and empower citizen scientists, enabling them to participate in increasingly difficult or domain specific tasks (e.g., hypothesis formation, data analysis). The possibilities for HI and AI to augment workers by (i) freeing up resources, so humans can use their expertise for further innovation, working on more cognitively demanding or rewarding tasks that computers cannot solve (Bresnahan et al., 2002) and (ii) introducing new demands and facilitating the acquisition of new skills that are necessary after the way of working has been transformed (Spenner, 1983) have been reviewed in Rafner et al., 2022, but it has not been investigated comprehensively in CitSci.

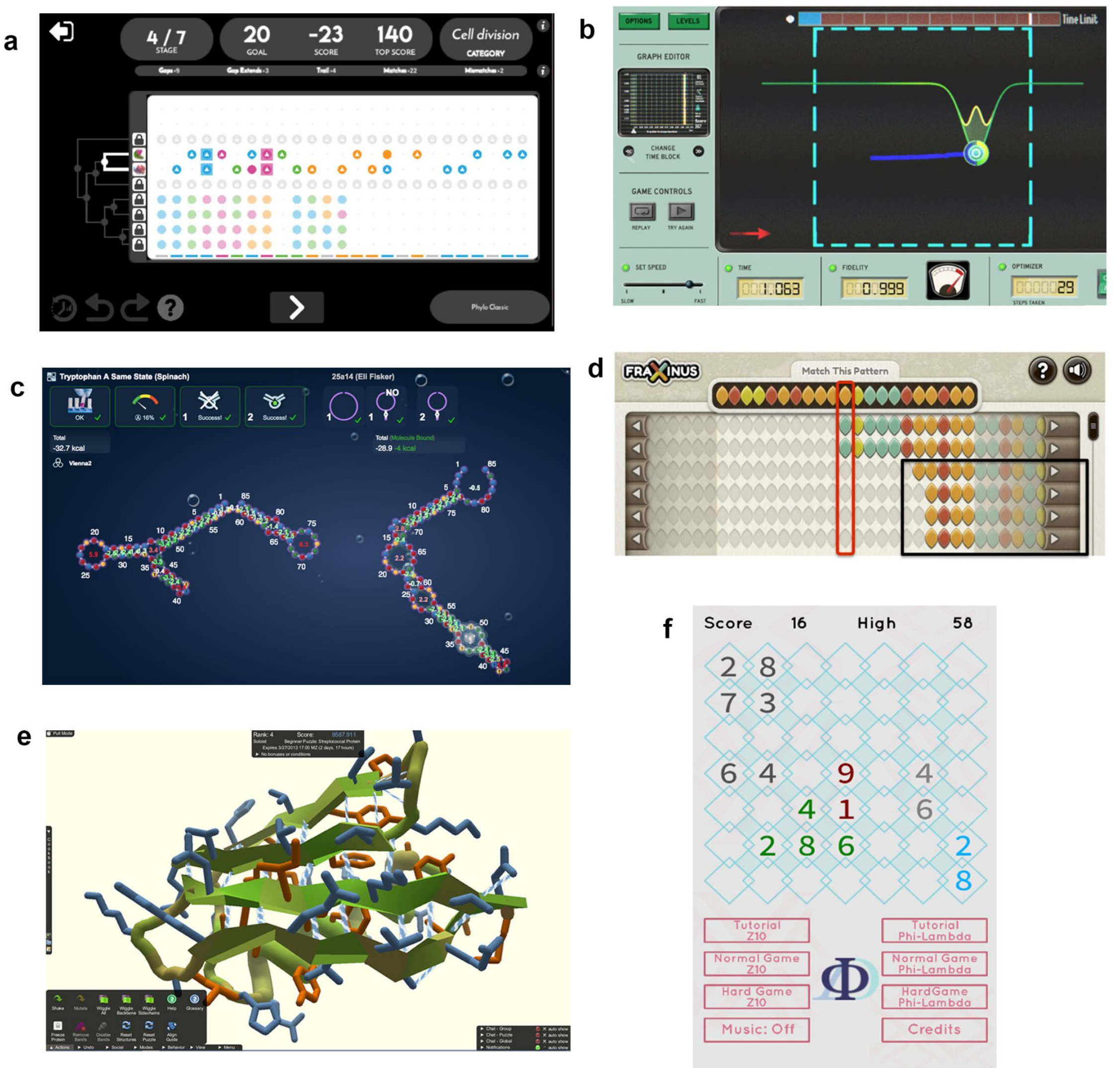
In conclusion, areas of great potential for human augmentation are applications of RL to optimization challenges, SL to annotation tasks, and smart sensors to participatory sensing tasks. However, advanced human-AI interaction typically tap into common sense, hierarchical thinking or meta-cognitive reflection and full human-level mobility combined with environmental sensing and domain knowledge. In future work, we encourage researchers to examine each of these categories more granularly to e.g., distinguish within the annotation category between image recognition tasks requiring computer vision and text recognition requiring natural language processing.

We conclude our article by offering five exciting research questions linking the fields of CitSci and AI:

i. Can the skill requirements of ongoing CitSci projects be interpreted as a continually updated 'thermometer' of the boundary between human and AI capabilities?
ii. What are the links between the accessibility of concrete CitSci tasks and the particular cognitive processes required to complete them?
iii. What are pathways, frameworks and quantification methods for participants to be upskilled during citizen science tasks through AI?
iv. How can the explicit task formulations in CitSci lead to increased understanding of human-AI interaction beyond the CitSci field?
v. Can the explicitation of the vast amount of CS-tasks that are at present not automatable yield greater appreciation for CitSci as a field and be used to increase participant motivation and sense of achievement?

Addressing these five questions will require new interdisciplinary partnerships and qualitative and quantitative research analyzing and developing individual CitSci and other related AI projects, understanding the core motivations and preferences of CitSci participants, as well as understanding attitudes to human-AI partnerships and CitSci in research and society.

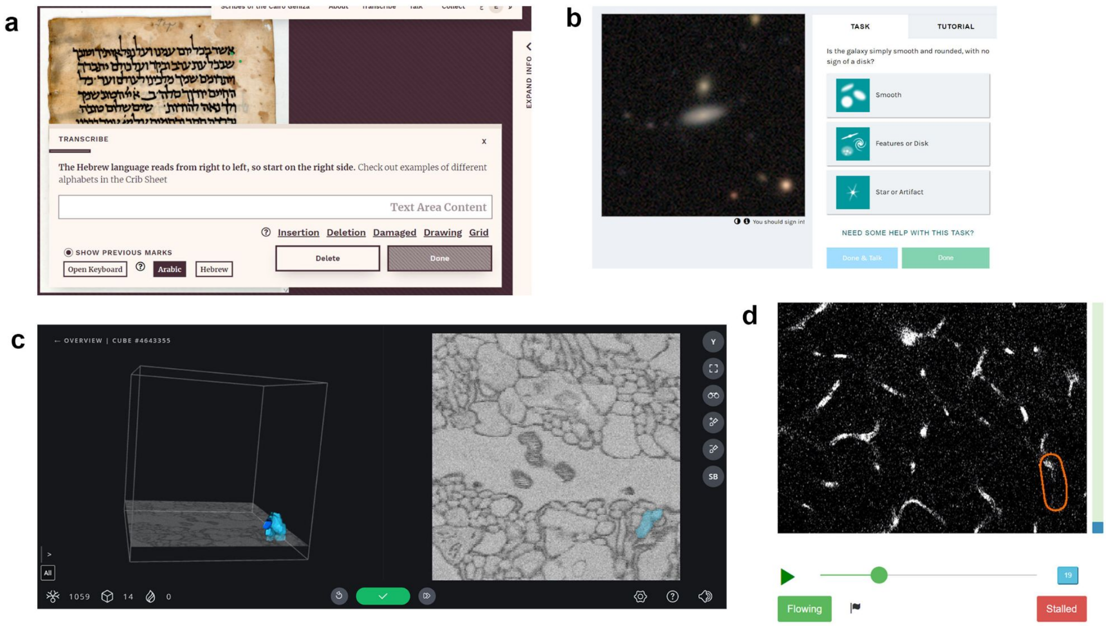
5. SUPPLEMENTAL FILES LIST



<u>Supplement 1</u>. Screenshots of optimization tasks. (a) Phylo (Phylo 2021). (b) Quantum Moves 2 (Ahmed n.d.). (c) Eterna (Eterna 2018). (d) Fraxinus (Rallapalli 2015). (e) Foldit (Foldit n.d.). (f) Decodoku (Decodoku 2021).

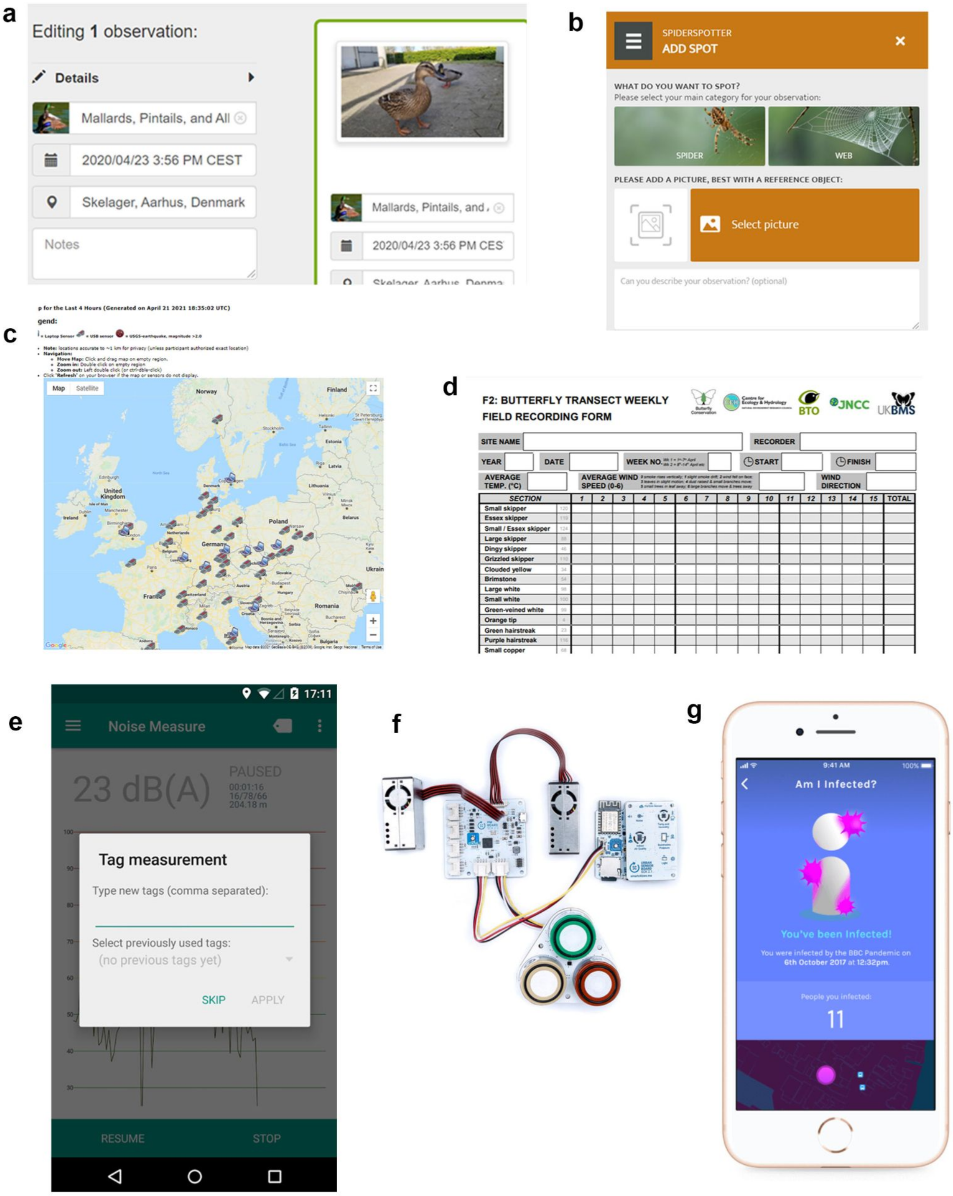
Supplement 1: Screenshots of optimization tasks. (a) Phylo (https://phylo.cs.mcgill.ca/play.php). (b) Quantum Moves 2 (https://www.scienceathome.org/games/quantum-moves-2/about-quantum-moves-2). (c)

Eterna (https://eternagame.org/news/8997813?sort=blog). (d) Fraxinus (Rallapalli 2015). (e) Foldit (https://fold.it/portal/info/about). (f) Decodoku (https://decodoku.itch.io/decodoku)



<u>Supplement 2.</u> **Screenshots of annotation tasks. (a) Scribes of the Cairo Geniza (Scribes of the Cairo Geniza 2021). (b) Galaxy Zoo (Galaxy Zoo 2021). (c) Eyewire (Eyewire 2021). (d) Stall Catchers (Stall Catchers 2020).**

Supplement 2: Screenshots of annotation tasks. (a) Scribes of the Cairo Geniza https://www.scribesofthecairogeniza.org/). (b) Galaxy Zoo (https://www.zooniverse.org/projects/zookeeper/galaxy-zoo/classify). (c) Eyewire (https://eyewire.org/). (d) Stall Catchers (https://stallcatchers.com).



Supplement 3. Screenshots of physical tasks. (a) iNaturalist (iNaturalist 2021). (b) Spider Spotter (Spider Spotter 2021). (c) Quake Catcher (Quake Catcher n.d.). (d) UK Butterfly Monitoring Scheme UKBMS (UKBMS, n.d.). (e) Noisetube (Noisetube 2021). (f) Smart Citizen (Camprodon et al., 2019). (g) BBC Pandemic (Manson, n.d.).

Name	General project description	Core participant task	Web reference
		Annotation tasks	
Galaxy Zoo	Classification of images of galaxies based on an evolving scheme devised by scientists who use the resulting classifications as part of their studies (Ponti et al., 2018).	Classifying images of galaxies based on particular features in a decision tree	https://www.zooniverse.org/projects/zookeeper/galaxy-zoo/ Ponti, M., Hillman, T., Kullenberg, C., & Kasperowski, D. 2018. Getting it Right or Being Top Rank: Games in Citizen Science. *Citizen Science: Theory and Practice, 3*(1): 1. DOI: https://doi.org/10.5334/cstp.101
Eyewire	Mapping the 3D structure of neurons in the brain and reconstructing neural circuits (Explore, Eyewire, n.d.) from serial electron microscope images (Eyewire, Wikipedia 2020) to discover how neurons connect and network to process information.	Solving 2D and 3D puzzles: Identifying and coloring axons of neurons in 2D view of 3D cubes using microscope images and pattern recognition skills	https://eyewire.org/explore Explore. n.d. Eyewire. Available at https://eyewire.org/explore [Last accessed 21 April 2021] Eyewire. 2020. Wikipedia. Available at https://en.wikipedia.org/w/index.php?title=Eyewire&oldid=950539218 [Last accessed 21 April 2021]
Stall Catchers	An online game that helps to speed up Alzheimer's disease research by making it possible for anyone to analyze microscopic images of blood vessels in the brains of transgenic Alzheimer's mice (Join a Global Game That's Trying to Cure Alzheimer's, Stall Catchers, n.d.).	Looking at movies clips from the brains of mice and trying to identify blood vessels as flowing or stalled (clogged)	https://stallcatchers.com/main Join a global game that's trying to cure Alzheimer's. n.d.. Stall Catchers. Available at https://stallcatchers.com [Last accessed 21 April 2021]
		Optimization tasks	
Quantum Moves	Finding the optimal solution for Quantum Mechanics evolution of wavefunction in a dynamical potential in the shortest possible time/duration. (Jensen et al., 2021, p.4).	Transferring atoms the best possible way from a specified initial state to the desired target state within very short timescales	https://www.scienceathome.org/games/quantum-moves-2/ Jensen, JHM., Gajdacz, M., Ahmed, SZ., Czarkowski, JH., Weidner, C., Rafner, J., Sørensen, JJ., Mølmer, K., Sherson, JF., 2021. Crowdsourcing human common sense for quantum control. *Physical Review Research*, 3(1): 013057.

			DOI: https://doi.org/10.1103/PhysRevResearch.3.013057 Quantum Moves n.d. ScienceAtHome. Available at https://www.scienceathome.org/games/quantum-moves-2/ [Last accessed 21 April 2021]
EteRNA	Capitalizing on the collective intelligence of EteRNA players to answer fundamental questions about RNA folding mechanics (EteRNA, CitizenScience, n.d.): Understanding and mastering the synthesis of RNA molecules and the RNA conformation for multiple medical, therapeutic and biotechnological applications (Lafourcade et al., 2015, p.5).	2D puzzle solving game with the four bases of RNA: designing elaborate structures, including knots, lattices and switches (EteRNA, Eterna, n.d.)	https://eternagame.org/home/ EteRNA. n.d. CitizenScience..Available at https://www.citizenscience.gov/eterna/ [Last accessed 21 April 2021] Eterna. n.d. Eterna. Retrieved Available at https://eternagame.org/ [Last accessed 21 April 2021] Lafourcade, M., Joubert, A., & Le Brun, N. 2015. Games with a Purpose (GWAPS). 1st ed. Hoboken, New Jersey, USA: John Wiley & Sons Ltd. DOI: https://doi.org/10.1002/9781119136309
FoldIt	Crowdsource problems in protein modelling: Creating predictive models of three-dimensional structures of proteins from their amino acid composition (Lafourcade et al. 2015, p.2) to understand how a mutation occurs at the level of the spatial conformation, and develop appropriate therapies (Lafourcade et al. 2015, p.2).	Protein folding puzzle game: players are presented with an unstructured amino acid sequence and challenged to determine its native conformation (Koepnick et al. 2019, p. 390)	https://fold.it/ Foldit. n.d. Foldit. Available at https://fold.it/ [Last accessed 21 April 2021] Koepnick, B., Flatten, J., Husain, T., Ford, A., Silva, DA., Bick, MJ., Bauer, A., Liu, G., Ishida, Y., Boykov, A., Estep, R.D., Kleinfelter, S., Nørgård-Solano, T., Wei, L., Players, F., Montelione, G.T., DiMaio, F., Popović, Z., Khatib, F., Cooper, S., Baker, D. 2019. De novo protein design by citizen scientists. *Nature* 570: 390–394. DOI: https://doi.org/10.1038/s41586-019-1274-4 Lafourcade, M., Joubert, A., & Le Brun, N. 2015. Games with a Purpose (GWAPS). 1st ed. Hoboken, New Jersey, USA: John Wiley & Sons Ltd. DOI: https://doi.org/10.1002/9781119136309
Decodoku	2-D puzzle solving game simulating the build-up of unwanted quantum	Adding up the numbers in the grids, where multiples of 10 disappear and new	https://decodoku.com/ Decodoku. n.d..Decodoku. Available at https://decodoku.com/

	interactions in quantum computers to learn about the cognitive strategies and heuristics players use to correct these errors, which can later be used for improving algorithms used in quantum error correction (Scientists Need You to Join the Phi-Lambda Mission and Make Quantum Computers Work, Zmescience, n.d.).	errors may arise until the game is over, then the players can provide an explanation on the thought processes and strategies they used during playing.	[Last accessed 21 April 2021] Scientists need you to join the Phi-Lambda mission and make quantum computers work. (n.d.). Zmesciece. Available at https://www.zmescience.com/science/physics/phi-lambda-mission/ [Last accessed 21 April 2021]
Fraxinus	Fighting the Ash dieback disease, a disease of ash trees, by identifying regions of DNA sequences that show characteristics like resistance, which might then be bred into a new disease-resistant variety. (Tsouvalis 2015, p.2).	A pattern-matching Facebook game: players aim to find the best match between color patterns	https://teamcooper.co.uk/work/fraxinus/ *Fraxinus*. n.d. Team Cooper. Available at https://teamcooper.co.uk/work/fraxinus/ [Last accessed 21 April 2021] Tsouvalis, J. 2015. How social and citizen science help challenge the limits of the biosecurity approach: The case of ash dieback. Available at https://blogs.lse.ac.uk/politicsandpolicy/limits-of-biosecurity-ash-dieback/ [Last accessed 21 April 2021]
Phylo	A game about multiple sequence alignment optimization: Players solve pattern-matching puzzles that represent nucleotide sequences of different phylogenetic taxa to optimize alignments over a computer algorithm (Play Phylo, Solve DNA Puzzle and Help Genetic Disease Research, Citizen Science Games, n.d.).	Solving pattern-matching puzzles of colored blocks: maximizing color matches across columns for best vertical alignments while minimizing gaps within sequences.	https://phylo.cs.mcgill.ca/ Play Phylo, solve DNA puzzle and help genetic disease research. n.d.. Citizen Science Games. Available at https://citizensciencegames.com/games/phylo/ [Last accessed 21 April 2021] Phylo DNA Puzzle. n.d. Phylo. Availabe at https://phylo.cs.mcgill.ca/ [Last accessed 21 April 2021]
		Physical tasks	
iNaturalist	A community of scientists, naturalists and citizen scientists and tools to create research quality data for scientists working to better	Recording and sharing observations of the nature using an app	https://www.inaturalist.org/ About. n.d. iNaturalist. Available at https://www.inaturalist.org/pages/about [Last accessed 21 April 2021] INaturalist.(n.d.. iNaturalist.

	understand and protect nature. (About, iNaturalist, n.d.)		Available at https://www.inaturalist.org/ [Last accessed 21 April 2021]
Smart Citizen	A kit to collect data and a platform to connect people to collectively address and find solutions to local environmental problems (Smart Citizen, Smart Citizen, n.d.).	Recording real-time environmental data and share it with the community	https://digitalsocial.eu/case-study/9/smart-citizen *Smart Citizen*. N.d. Smart Citizen Available at https://digitalsocial.eu/case-study/9/smart-citizen [Last accessed 21 April 2021]
UK Butterfly Monitoring Scheme	Monitoring changes in the abundance of butterflies throughout the UK based on a well-established and enjoyable method to understand trends in insect populations and answer policy questions relating to status and trends in biodiversity. (Home, United Kingdom Butterfly Monitoring Scheme, n.d.)	Selecting site, designing route and recording and submitting data weekly (Pollard walks)	https://www.ukbms.org/ Home. n.d. United Kingdom Butterfly Monitoring Scheme. Available at https://www.ukbms.org/ [Last accessed 21 April 2021]
NoiseTube	Monitoring noise pollution to inform the community, create collective, city-wide noise maps, improve policy making with regards to noise level, and research soundscape perception. (NoiseTube, NoiseTube, n.d.)	Monitoring noise level in surroundings using an app and tagging the measurements (e.g. subjective level of annoyance, source of sound)	http://www.noisetube.net/index.html#&panel1-1 NoiseTube. n.d. NoiseTube. Available at http://www.noisetube.net/index.html#&panel1-1 [Last accessed 21 April 2021]
Spider Spotter	Studying spider evolution in the city in real time how spiders adapt to the increased heat and other special circumstances in the city to inform research on climate change and potentially discover new ways to adapt to the changing environment (Info, SpiderSpotter, n.d.).	Taking pictures of spiders and/or their web with a reference object using a smartphone app and/or analyse photos on the website and calculate the color and length of the spider or web (Info, SpiderSpotter, n.d.).	https://www.spiderspotter.com/en/ *Home* n.d. Spider Spotter. Available at https://www.spinnenspotter.be/en/ [Last accessed 21 April 2021] *Info* (n.d.). Spider Spotter. Available at https://www.spiderspotter.com/en/info/spin-city [Last accessed 21 April 2021]

Supplement 4. Projects, descriptions, and sources.

Supplement 5. Related terms (see additional PDF)

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The author(s) has/have no competing interests to declare.

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