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Harnessing collective intelligence for the future of learning – a co-constructed research and development agenda

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ABSTRACT

Learning, defined as the process of constructing meaning and developing competencies to act on it, is instrumental in helping individuals, communities, and organizations tackle challenges. When these challenges increase in complexity and require domain knowledge from diverse areas of expertise, it becomes difficult for single individuals to address them. In this context, collective intelligence, a capacity of groups of people to act together and solve problems using their collective knowledge, becomes of great importance. Technologies are instrumental both to support and understand learning and collective intelligence, hence the need for innovations in the area of technologies that can support user needs to learn and tackle collective challenges. Use-inspired research is a fitting paradigm that spans applied solutions and scientific explanations of the processes of learning and collective intelligence, and that can improve the technologies that may support them. Although some conceptual and theoretical work explaining and linking learning with collective intelligence is emerging, technological infrastructures as well as methodologies that employ and evidence that support them are nascent. We convened a group of experts to create a middle ground and engage with the priorities for use-inspired research. Here we detail directions and methods they put forward as most promising for advancing a scientific agenda around learning and collective intelligence.

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1. INTRODUCTION

Today humanity faces a diverse and considerable range of challenges, but we also live in the era of growing opportunities. Climate change, biodiversity collapse, pandemics, and food and energy crises are just some examples. To help focus collective attention, the United Nations summarized the most important challenges in the Sustainable Development Goals (SDGs) Framework (UNGA, 2015). The framework emphasizes SDG 4.7 that targets supporting educational systems as means to address all of the seventeen goals. It might be argued that some of these challenges are far from novel and have accompanied humankind throughout its history (Ghorbani, 2020). Although such a position is warranted, contemporary societies have developed innovative technologies that support how individuals and collectives decide on the action needed to address shared challenges. Due to the scale and affordances of these tools, the actors interested in knowledge creation and practice change have become well positioned towards overcoming current challenges.

Learning can be defined in many ways (Qvortrup et al., 2016), but here we broadly describe it as the ability of biological, human, technological or hybrid systems to construct meaning and develop competencies to act on it. Learning can span individual and collective levels of a system (Fenwick, 2008). For individuals, learning is fundamental to survival and thriving. At the level of an individual, such learning encompasses mastery of multiple literacies and evolving domain knowledge, the development of capabilities needed in the modern workplace and regulation of one's well-being (Diener & Ryan, 2009). Individuals also need to develop personal skills for coexistence with each other and the environment (Hannon & Peterson, 2021). The emerging demands for literacy and skills, require that individuals learn throughout their lives, both within formal educational systems and outside of them. *Individual* learning helps humans acquire new knowledge and skills. Yet, when the challenges increase in complexity and require domain knowledge from diverse expertise areas, situations arise that might require *collective* learning to tackle them. Addressing these challenges requires bringing together diverse individual skills and perspectives both to learn collectively as well as to act collectively.

Collective intelligence has been touted as an important mechanism for solving pressing problems of our times (Nielsen, 2011). Multiple definitions of collective intelligence have been proposed, originally starting as the intelligence that emerges from the collaboration and competition of many individuals (Lévy, 1997). Current interpretations are either more broad, referring to a group's ability to find more or better solutions than those that would be found by its members working individually (Heylighen, 1999; Leimeister, 2010), a group's ability to perform and solve problems and the process by which this occurs (Michelucci, 2013; Woolley et al., 2015) or groups of individuals doing things collectively that seem intelligent (Malone & Bernstein, 2015). Crowdsourcing can be seen as a special case of collective intelligence (Buecheler et al., 2010). Mulgan goes back to Latin origins of the word intelligence ('inter' meaning 'between', and 'legere' meaning 'to choose') to emphasize the importance of group formation - who we act with and not just how we act (Mulgan, 2017). Some even argue that existing definitions are not in conflict but only describe the same phenomenon seen through different disciplinary lenses (Galesic et al., 2022). Here, we define collective intelligence as decisions taken when large groups of people construct meaning, with the emphasis on the collective ability to act on it.

Thus far, technologies have played a dual role in the processes related to learning and collective intelligence. On the one hand, new tools promise to help solving existing crises and other complex problems, due to scale, breadth, and speed of information dissemination, potentially amplifying access for learning (Masselot et al., 2022; Rafner et al., 2022). Digital tools further collect data about the processes of learning and collective intelligence, revealing insights about individual and collective dynamics (Chen et al., 2021; Lazer et al., 2020). Artificial Intelligence (AI) based algorithms trained with information specific to particular systems also offer a promise to personalize pathways for learning (Markauskaite et al., 2022) Furthermore, novel AI systems offer the opportunity to realize the idea of hybrid intelligence, meaning that human and artificial intelligence jointly can achieve results superior to the results human or artificial intelligence could achieve in isolation (Dellermann et al., 2021). On the other hand, the same tools might sometimes exacerbate human biases and human dynamics that destabilize these very processes. For instance, several competing arguments have been put forward about both the positive or negative effects of social media as tools of large collective coordination (Etter & Albu, 2021; Gao et al., 2011; Spier, 2017). Some authors have highlighted how this new space allows for decentralized organization, giving rise to projects such as Wikipedia, or new democratic organization, with online petitions raised as an illustrative example (Shirky, 2008). Other authors, however, have argued that new spaces reproduce previous organizational structures, reaffirming them and limiting the opportunities thought by enthusiasts of decentralization and self-organization brought about by digital transformation (Morozov, 2011). Finally, some scholars have even stressed that the new decentralized forms of governance come with significant ailments of their own (Benkler et al., 2018): the lack of gatekeepers tests our notions of truth in the "fake news era" (Albright, 2017) while hyper-connectivity and the democratization of speech test online cohabitation, with polarization, “echo chambers”, and “filter bubbles” gaining attention in research and policy communities.

The dual role that technologies play upholds the idea that new, innovative solutions need to cut across research and development areas. First, innovations need to offer practical tools that can directly address user needs and in turn support learning and collective intelligence that enable action. Second, conceptualizations and evidence explaining mechanisms behind learning and collective intelligence are just as needed as the tools that support these two processes. Critical examination and evidence are useful in providing rigor and governance for *where* and *how* technologies need to be designed, facilitated, and adopted. Innovations grounded in use-inspired research can address both needs for knowledge production and technological advancement. Use-inspired research – a research paradigm proposed by Stokes (Stokes, 2011)– rethinks the relationship between science and technology. Stokes describes research where scientific worth and practical usefulness intersect as *Pasteur's quadrant*, emphasizing the need for inquiries where “basic research sought to extend frontiers of understanding and was inspired by considerations of use”, p. 74 (Stokes, 2011).The need for use-inspired research exists within a larger context of eroding trust in scientific and governing institutions. The latter implies that new knowledge paradigms, such as use-inspired research, are also in need of values around how science is conducted: open science and citizen science are one possible response to this need (Haklay et al., 2021).

Several recent theoretical frameworks explaining collective intelligence processes, and linking them with learning by individuals and collectives, have been proposed. For instance, building on interdisciplinary lenses inspired by natural collective systems, Flack has theorized the relationship between information processing by individual species and collectives enables both individual and collective action (Flack, 2012, 2017). Existing learning theories also allow to nest various levels of learning, to multiple scales and levels of the systems that learn (Kapur et al., 2007; Markauskaite & Goodyear, 2017)**.** Bridging complexity science with cognitive sciences, Galesic and colleagues extend the notion of collective intelligence to that of collective adaptation (Galesic et al., 2022)**.** According to this theorization, the scientific focus has to cut across three blocks, each being its own field of study, namely: problem space mapping, cognitive strategies to solve a problem, and social networks of cooperation. From this theoretical view, groups need to collectively adapt to different problem types, hence research inquiries need to ponder about combinations of cognitive strategies (e.g., consensus building rules) and social network structures best suited to solve a particular problem (e.g., exploration vs exploitation). Technological infrastructures and evidence aligned with most of the views on collective intelligence are nascent. Technological systems for learning are more mature, but lack deeper analysis of case-studies and designs to promote equity and agency development, as well as evidence-based solutions for learning as self-improvement (Harvey, 1995). In short, gaps in science and technology for learning and collective intelligence persist.

Creating knowledge and tools that help support learning and collective intelligence is a compelling agenda for those working on the edges of knowledge production and practice change. By employing collective intelligence to improve learning we strive to build a certain vision of the society's future. However, to be able to properly define the most relevant challenges and propose a path towards solutions, we must define the type of future we wish to reach. The vision presented here is but an outline, in the long run it should be framed and detailed though a more comprehensive policy, legal, and multilateral discussion.

We start with the premise that this future should attend to both societal and the individual needs, and should see both thrive. Broadly speaking, we see a thriving individual as one who is healthy, both mentally and physically. Humans have evolved to seek 'self-actualization', defined by Maslow as 'self-fulfillment', namely the tendency for the individual to become actualized in what he is potentially (Maslow, 1943). This tendency might be phrased as the desire to become more and more what one is, to become everything that one is capable of becoming'. As humans we seek to receive recognition for our work and strive to have a meaningful life, which includes creativity, a sense of purpose and belonging, including but not only related to work (Hannon & Peterson, 2021). To achieve these goals, humans need to be pursuing and acquiring wisdom and not just knowledge or information (Bierly III et al., 2000). This way, we acquire the competencies necessary for thriving in a globalized world, such as global competence (OECD, 2018) self-reflection and critical thinking. A thriving society is one with thriving citizens, but also additional emergent properties. It is a peaceful one (i.e., resolving conflict in a non-violent way) that must update the idea of enlightenment for the digital age, to include both public debate, broad involvement in democracy, collective decision-making while ensuring inclusivity, respect for personal freedoms, equity and acceptance of cultural diversity. Part of this equity is the duty to recognize wisdom already known by societies around the globe and recognize the collective duty to ensure that all societies benefit from advances made towards a thriving planet. Composed of self-critical, well-informed citizens, the thriving society is a global one, where everyone, including the youth, is equal. The thriving society is open and innovative, capable of collective intelligence for good, and will be achieved by moving from competition to cooperation between its participants (Pickett & Wilkinson, 2010).

Finally, our vision of the future goes beyond human society, to incorporate humility and acknowledge we are only a part of an interconnected ecosystem (Lovelock & Margulis, 1974). Our future must be a sustainable one that meets the needs of other species and the planet. These goals help us formulate the themes and the challenges for collective intelligence in and for learning. Of course, the agency rests with the society and all its participants to redefine and update this vision, adapting it to challenges and opportunities of the future.

Determining the design of global social systems, aligning goals of and for a society requires thorough consideration of constitutive elements such as human rights, economic growth, political systems, conflict resolution, among others. The full framing is beyond the scope of this paper and the collective competencies of its authors. However, the first draft of such a target was necessary for the purpose of our work here and we hope it serves as an invitation to others to refine it further. We used it to guide the collective discussions during a four day in person workshop, during which we have identified key areas where innovative solutions in the form of research and development need to be prioritized to support learning and collective intelligence.

2. METHODS

This article is the outcome of the workshop held April 12 to 15, 2022, at the Learning Planet Institute (formerly Center for Research and Interdisciplinarity, CRI). The workshop was organized as part of the process to strengthen and position the Learning Planet Institute as a middleground, a space that brings together a range of stakeholders that carry diverse perspectives on learning and collective intelligence (Cohendet et al., 2010). The specific goals of the workshop were twofold: (1) identify key priority challenges in the advancement of learning and collective intelligence that can be solved through innovative use-inspired research, and (2) propose concrete examples of problems that research and development solutions can solve to push forward collective action around these priority challenges. Here we detail the process of design, organization, and execution of the workshop, all the way to production of this paper.

2.1 Participants.

To achieve the workshop goals, we assembled an invite-only group of 35 experts in the areas of learning and collective intelligence who engaged in a knowledge production process over four days of on-site work. We started by identifying internal and external experts who could serve as co-organizers of the workshops. Having multiple co-organizers with different backgrounds assured a more broad, comprehensive approach to both participant selection and workshop design. We continued by inviting people from our network, and some experts we wished to connect with for the first time, but interestingly, a number of the final participants were two or three degrees of separation away, recommended by people who we invited but could not attend. We were consciously seeking to convene a diverse and representative group of participants, inclusive and balanced across different axes, such as stakeholder type, career stage, gender, and competencies. Besides representing a range of viewpoints, approaches, and knowledge, we considered this diversity to be one of the main benefits for the participants themselves. Many of them indeed cited the chance to meet and have sustained, meaningful discussions with experts outside their academic or professional bubbles as extremely rewarding.

2.2 Workshop format and dynamics.

The workshop discussion and co-creation approach was co-designed with the co-organizers and based on experiences from previous workshops that organized by the Learning Planet Institute since 2017, which also resulted in position and opinion papers (Bafeta et al., 2020; Kusters et al., 2020).

As in the past, we prioritized discussion and writing over frontal presentation. Similarly, we focused on considering the short and long-term future prospects, rather than the past accomplishments. To do so, the only presentations were in the format of 2-minute flash talks, supported by at most a single slide each. Additionally, we prompted participants to share their knowledge and opinions by answering motivating questions like “What is your vision for the field in the next 5-10 years" and “What cannot be done yet (open questions)?”. The responses were collectively synthesized, and different opinions clustered into major topics that are eventually became the subsections of the Result section of this paper. All this was accomplished during the first workshop day. The second day focused on proposing research and development-based solutions to the challenges identified and clustered on the previous day. This was first done using a World Cafe methodology (Löhr et al., 2020), allowing everyone to contribute to discussion on all the topics. The second half of the day was spent in focused discussion, where participants chose one specific topic to contribute to and discuss in depth. The third day, and part of the fourth day were spent on writing this paper, specifically focusing on the challenges presented in the results section. Each challenge was analyzed using the following questions as prompts, “What is the challenge?”, “What might be the underlying causes?”, “What is the desired final situation?”, “What is the proposed initiative?”, “What does this initiative add to the state of the art?”, “What research solutions can be offered to advance tackling the challenge?”, “What development solutions can help tackle (parts of) the challenge?”, “What are the scales/ system levels that the solutions can act upon?” (e.g. of local -> global/micro (individual)-meso-macro (country/planet)), “What is the timescale at which this solution can act?”, and “How is the solution positioned in the applied-to-theoretical/Pasteur’s quadrant space?” The list of questions was not always strictly followed, but was used to channel the discussion and make work done by different groups more coherent.

The afternoon of the fourth day was dedicated to the oral presentation of the workshop discussion and outcomes. The presentations served as a workshop conclusion, but also as a bridge to the local community. By welcoming university leaders, researchers, students, funding agencies, and entrepreneurs, we both sensitized them to our thinking and approach and we hopefully opened additional possibilities to actually address the challenges we defined.

2.3 Workshop outcomes.

The most tangible workshop outcome is this paper itself. The first, rough draft was written during the workshop, using a collaborative online Google document, starting from a general paper outline prepared by the co-organizers. Initially, workshop participants spent time working on a section of their interests. This was followed by a round of edits and feedback from all the participants on the entire manuscript. The writing and editing continued asynchronously and remotely in the months following the workshop, coordinated by the workshop co-organizers, and with one person being a point of contact for each results section. Co-organizers wrote the abstract, intro and discussion. Beyond the paper itself, this workshop was of course a networking event. Many of the participants found new connections with people in adjacent fields, and were challenged to extend and apply their competencies to new domains. Creating new collaborations or jointly targeting funding possibilities was not an explicit intention, but both have materialized since the workshop.

Our methodology created a space that enables diversity of opinions and expertise to connect, reflect, and work together. It led to a tangible outcome, this paper, which can communicate both the methodology and conclusions of the workshop. Our approach is topic-agnostic, and can easily be adapted to other topics in order to provide a basis for similar identification of relevant challenges and potential research directions.

3. RESULTS

Following our workshop methodology, we identified five focal themes that assemble the most relevant and timely challenges that can be advanced at the intersection of learning and collective intelligence. In Theme 1 we discuss general questions about the process and goals of learning, especially in light of our ever-changing society. In Theme 2 we address specific approaches to learning which are both collective and aided by technology. In Theme 3 we return to the learners themselves rather than learning tools by focusing on social and emotional learning. Theme 4 analyzes the challenges related to evaluation and assessment of learning, specifically in informal learning. Finally, in Theme 5, we zoom out and consider how to affect systemic change in the area of learning and collective intelligence. In each case, we provide a brief introduction and description of the topic, followed by the analysis of at least one specific challenge. This is of course not an exhaustive list, but a reflection of the assembled community of diverse actors that drafted it.

3.1 Theme 1: Processes, goals, and values of learning in the 21st century

In 2020, 46.5%[1,2] of students who had enrolled in the first year of a Bachelor program at French public universities didn't register for the second year (Evans & Cosnefroy, 2013) while the estimated annual cost by student is now higher than 10k€[3,4]. At the same time, the national rate of

[1] https://www.lesechos.fr/politique-societe/societe/universites-le-taux-de-reussite-en-licence-a-fait-un-bond-en-avant-1366475, accessed 20/2/2023
[2] https://www.enseignementsup-recherche.gouv.fr/sites/default/files/imported_files/documents/NF22_Reussite_Licence_1343710.pdf, accessed 20/2/2023
[3] https://www.education.gouv.fr/en-2019-le-cout-moyen-par-etudiant-est-de-11-530-euros-322990, accessed 20/2/2023
[4] https://www.cae-eco.fr/enseignement-superieur-pour-un-investissement-plus-juste-et-plus-efficace, accessed 20/2/2023

unemployment in France currently stands close to 8%[5,6], in part because people lack the skills required for the job market of the 21st century. These two statistics may influence the allocation of public funds and highlight a substantial barrier to people living fulfilling and productive lives. They represent a failure to understand and support the conditions that learners need in order to be more effective, engaged and resilient, both in formal education and in wider life. Lack of interest or passion in the studies may be one of the highest factors impacting intention to dropout. (Piepenburg & Beckmann, 2022; Zhao et al., 2021). Moreover, among the 18 OECD countries for which data are available, some 31% of students who enter tertiary education leave without a tertiary qualification (OECD, 2010). This problem continues outside university education, to include technical and vocational education, performing and visual arts, ultimately contributing to 13.1% of the 15-29 year-olds in the EU in 2021 being neither in employment nor in education and training[7]. Below we highlight three key interrelated challenges, where research can shed light on these mechanisms and have a profound impact on education and economic performance.

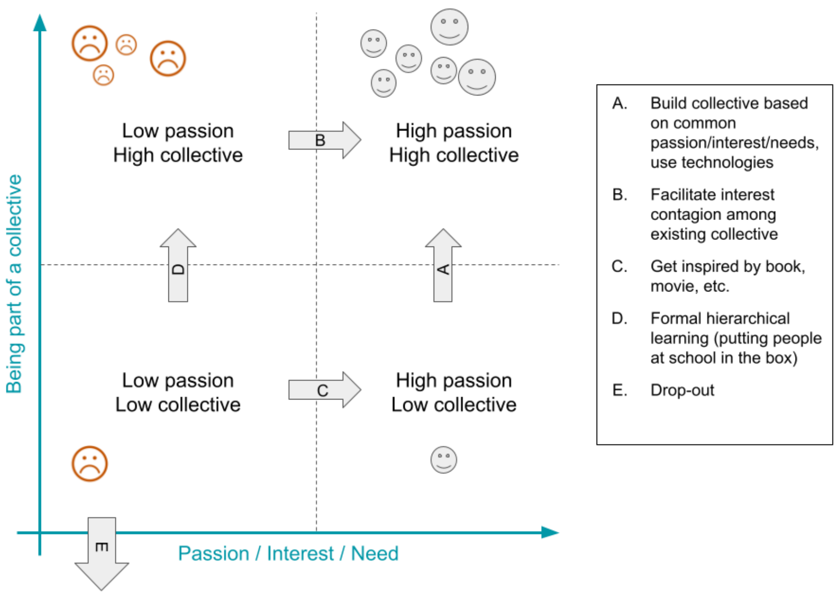
3.1.1 ***Challenge 1.1.*** *How to make people more engaged in learning?*

In today's attention economy, keeping learners' attention and motivation in class and in learning is an important challenge that needs to be addressed (Barkley & Major, 2020; Finn & Zimmer, 2012). Motivation, both intrinsic and extrinsic, is an important predictor of learning and achievement. Students who are more motivated to learn persist longer, produce higher quality effort, learn more deeply, and perform better in classes and on standardized tests[8] (Hulleman, 2018, Robbins 2004) Learners who are more motivated are better equipped to thrive in school and throughout their lives, but teachers often struggle to engage learners and keep them motivated within class and throughout the school year. Any levers that help teachers instill in their students an eagerness to learn would benefit the students.

We propose that a critical factor in engagement is the social connection of the learner with their peers, mentors, teachers, or instructors. This builds on past literature highlighting the effectiveness of peer-based learning practices(Stevenson, 2018; K. Topping et al., 2017; K. J. Topping, 2005). There have been many attempts to reduce attrition based on reacting to learners' struggles (low grades, not attending courses). A systematic study of social networking interventions in education could simultaneously build on and advance research in computational social sciences and complex contagion models (Centola, 2018) as well as in recommendation systems and machine learning.

[5] https://tradingeconomics.com/france/unemployment-rate, accessed 20/2/2023
[6] https://data.world/databeats/college-completion , accessed 20/2/2023
[7] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Statistics_on_young_people_neither_in_employment_nor_in_education_or_training , accessed 20/2/2023
[8] https://www.future-ed.org/reversing-the-decline-in-student-motivation, accessed 20/2/2023

Learners who feel isolated or disconnected are less able to overcome learning challenges and draw upon the support that maintains their interest in the subject. Conversely, passion and interest can be contagious, and strong social bonds can help sustain these, mainly where strong social connections exist between learners with differing levels of engagement. Finally, well-connected learners can quickly identify with their learning program (meaningfulness of the program), thus developing a drive towards competence that can overwhelm learning obstacles. The diagram in Figure 1 provides a view of feature space relevant to our problem as well as the illustration of a variety of challenges of learning objectives and values. This includes engaging people to be passionate about learning (arrows A, C), developing “learning how to learn” skills (arrow C), retraining the workforce for the jobs needed for the future (arrows A, B, C, D) and prevention of drop/out from learning engagement (arrow E).



<u>Figure 1.</u> Quadrants of motivation vs. individual-collective applied to the context of learning.

We want to develop a collective sense of belonging and connection between learners such that they are motivated by a contagious drive and passion, which leverages the initial interest of the most engaged learners to support wider engagement. In essence, we want learners to consider it important to themselves that they are gaining expertise, and to support this by making the subject part of their social identity - something that unites them with people they have rewarding social ties with. We propose two possible ways to develop connections between learners: (1) providing a framework and activities for the learners to form a support network and using recommendation algorithms to match learners based on common interests and (2) using network science modeling to examine the spread of passion within networks.

In order to form a support network of learners we recommend starting by asking them to reflect on and share their motivations for learning (formal and informal). Recommendation algorithms can use this data to match learners of similar motivations and interests and give them the opportunity to mingle together by e.g., putting in the same dorms, organizing common activities, etc. These interventions should lead to the formation of support networks for learning in which learners can ask other network members to help them on a day-to-day basis or in moments of distress. The network members can be their peers but also other people like family, friends, colleagues, and mentors. One example of such a support network example is the Madagascar network of learners[9], where learners are engaging and connecting to each other using phone networks. The idea is to couple behavior modeling and applied interventions, and then proceed iteratively to improve the model based and the associated interventions.

Using the data from these interventions we propose constructing a social contagion model to model how learners' interests and passions spread in communities. Models of complex social contagion on social networks will be implemented to understand how common interests and passions spread throughout a network of university learners. The hypothesis we want to test is whether passion is contagious. Are low motivation individuals positively affected by interacting with individuals with high levels of motivation? The results will lead to the construction of "learning comfort zones", favoring engagement and passion spread. These solutions will first address local communities/universities but since they are network based, they could be scaled up to other, greater, or less formal communities of learners.

3.1.2 ***Challenge 1.2.*** *How to develop "learning how to learn" skills?*

Problems facing the young generation are increasingly new and solutions are likely to be non-routine. However, we carry a heritage of older, traditional educational systems where learning meant simply and often only "learning from the textbook". In an exponentially expanding knowledge space one needs new strategies for learning. We believe this requires a shift to a new learning paradigm defined by greater learner autonomy, choice and engagement - including the autonomy to select one's own advisors, own ways for learning, and diverse sources of information. In practical terms, we anticipate a future educational system in which learners undertake more self-directed and self-defined projects, potentially under the mentorship of an educational professional, rather than one in which a lecturer transmits a pre-defined syllabus of information to a passive learner. We propose to understand the personal, environmental, and organizational factors that predict this engagement and thus create guidance for producing successful programs. We specifically focus on the challenge of creating new tools and open environments where "learning how to learn" would be supported.

[9] https://interactiondatalab.com/collaborative-learning/, accessed 20/2/2023

In order to “learn how to learn”, we propose implementing experiential learning courses**,** mandatory at the start of bachelor programs**.** These courses would be designed explicitly to equip learners with both cognitive tools for self-directed learning (e.g., how to find and evaluate information, how to confront and overcome learning obstacles) and also to set the context and expectations for self-directed learning throughout the rest of the syllabus (i.e., introducing and explaining the reason for more autonomous ‘mentored’ learning, as opposed to the passive learning style likely experienced at school). They could also include other currently-under emphasized skills such as rhetorical and theatrical performance. Some digital tools open for the augmentation and integration of facilitation techniques have already been developed or prototyped and could be used to support this initiative [10,11,12,13,14]. We envisage developing additional tools that allow the learner to track their progress and self-improvement, as well as to assess their learning outcomes, possibly relying on multi-dimensional digital representations of knowledge space that includes interconnected info on various documents, articles, and subjects of learning.

“Learning how to learn” is of course a meta-skill that should be embedded throughout the syllabus and beyond formal education, but requiring it at the start of an educational program is a useful stepping stone toward this goal, with three key benefits: (1) focusing on formal education allows us to test an intervention and demonstrate the efficacy of the philosophy in a more controlled setting; (2) it requires a less open-ended effort on the part of staff and reduces potential disruption to the syllabus when the effect is unknown; and (3) by creating a defined and limited intervention, it allows for greater statistical certainty about the effect of this initiative when evaluating its impact on key metrics such as learner retention after the first year and final exam performance. With this defined intervention we can also dig deeper into the specific factors that drive engagement by conducting a randomized controlled trial across universities, matched for demographics, geographic location and academic performance, by manipulating the training offered to learners in activities aimed at a deeper understanding of their strengths, drives and communication skills. An active control should include the same offering to learners but in the form of elective non-mandatory training. This approach embodies action-driven research, with fundamental research on educational outcomes directly informing and directing actions to improve “learning how to learn” skills.

[10] Super Skills Lab - https://medium.com/@thebuidler/super-skills-a-mobile-application-use-case-for-dids-and-vcs-d174467ccf46, accessed 20/2/2023
[11] WeLearnRecsys - https://projects.cri-paris.org/projects/adsaYHsn/summary, accessed 20/2/2023
[12] WeLearn, currently under development at http://learningplanetinstitute.org, accessed 20/2/2023
[13] Skills - https://projects.cri-paris.org/projects/bsHSydgN/summary, accessed 20/2/2023
[14] Projects - https://projects.directory/discover, accessed 20/2/2023

3.1.3 ***Challenge 1.3.*** *How to retrain the needed workforce for the present and future jobs?*

Retraining a workforce whose jobs will become redundant, often more senior workers, requires deep changes in the training and organization of work, both in terms of cultural acceptability of new behavior and in terms of economic incentives to cooperate. There has been research done on 'deskilling/upskilling/reskilling', in particular on hybrid intelligence and deskilling (Li, 2022; Rafner, Gajdacz, et al., 2021). This can also be construed as development of collegiality and breaking established hierarchies in otherwise bureaucratic hierarchical organizations (Laloux, 2015). For example, making it acceptable for older people to be mentored by younger ones, or for managers to not compete with their subordinates and to help the latter find collaborations, or let them find collaborations, likely to bring together complementary skills and promote innovations. The challenge is to co-construct the goals, ways and means to achieve such changes in the workforce with the workers themselves, rather than as part of abstract, externally designed training programs. Various examples of initiatives that break through classical hierarchies and established learning models include language courses for immigrants, where learning is happening independently from age or origin, and the "School in the Cloud" initiative[15], where students learn without a formal teacher role. Such initiatives can be replicated and serve as inspiration for designing other topics or in other contexts for life-long learning. Another way to shake up the established hierarchies and develop new skills is to rotate members of organizations so that teams always include an adapted balance of incumbents and novices focusing on problems to solve. Currently only 11% of adults in Europe participate in life-long learning[16]. New, co-constructed initiatives are needed to increase this statistic and ultimately encourage people to remain engaged learners throughout their life, in and out of the workforce, well after completing formal education.

3.2 Theme 2: Technology-augmented collective learning

Our societies and institutions are not adapting sufficiently fast to meet the Sustainable Development Goals and address existential risks posed by major planetary challenges (Rockström et al., 2009). Learners increasingly question the relevance and purpose of what they are learning. We need thriving, lifelong learners equipped to understand, make sense of and contribute to public, corporate, and individual planetary solutions. Inquiry-based, active, and collaborative methodologies have been explored in recent years (Friesen & Scott, 2013; Laal & Ghodsi, 2012; Löhr et al., 2020; Michael, 2006), but they are often difficult to implement at scale. While digital technologies can help scale their implementation (Tautz et al., 2021), designing the appropriate technologies for supporting learning is challenging. The main question that emerges is: How can technology support (and not hinder) learning experiences to collectively address future societal challenges? We identified four major challenges related to technology in learning: connecting learners, combining learning with activism, representing the learning process for reflection and

[15] https://www.outlookindia.com/website/story/india-news-why-school-in-the-cloud-will-be-our-new-normal/394341, accessed 20/2/2023
[16] https://ec.europa.eu/eurostat/web/products-eurostat-news/-/DDN-20190517-1, accessed 20/2/2023

action, and ensuring that systems are ethical, equitable, and explainable. Solving these challenges will require interdisciplinary research involving experts in social and learning sciences, citizen science, psychology, computer science, information systems and human computer interaction. Our proposed initiative represents use-inspired basic research that operates at individual and group levels to scale inquiry-based methodologies to the collective level.

3.2.1 ***Challenge 2.1****. How to connect learners?*

In the context of a technology-rich environment that supports collective intelligence, we need to be able to adaptively help people find peers or mentors to learn with. In some cases, this matching will result in one-time interactions where one learner helps another; in others, learners might go on to form sustaining relationships that then support and motivate them as they pursue their projects. There has been a significant amount of work on automatically matching and/or providing recommendations for group formation based on single factors that are often cognitive, e.g., complementary expertise or heterogeneous knowledge (Echeverria et al., 2020; Magnisalis et al., 2011), but little work has moved beyond this to consider the full range of potential characteristics that might be used to help find matches. However, within the context of collective intelligence we still do not know which exact combinations of learner characteristics and goals lead to productive and harmonious group interactions, in spite of work on collaborative learning patterns (Hernández Leo et al., 2005; Jermann & Dillenbourg, 1999), quality indicators of good collaboration (Meier et al., 2007), and prior work on recommender systems for defining learners models (Kleinerman et al., 2021). Thus, we pose the following specific research question: How do we build technology to help connect peers both for one-time interactions and sustainable engagements based on holistic criteria?

To address this question, we need to investigate (1) which learner characteristics to include as part of a matching algorithm, and (2) what matching algorithms and interfaces produce the most successful interactions on several criteria (e.g., what is the outcome of the interaction, how satisfied are learners, how likely are learners to go on to form a long-term collaboration). There is a need to develop a peer matching system to encourage and facilitate learners to share their individual projects and pursue collective work. This solution acts at (1) the individual level to support individual growth and relationship-building on our platform, (2) the group level to improve the quality of collective work, and then consequently (3) a macro-level to enhance the collective intelligence between groups. Pursuing this use-inspired basic research will both uncover fundamental principles surrounding group formation within this context and build a technology that reifies these principles to actively support learners in forming groups.

3.2.2 ***Challenge 2.2.*** *How to combine learning with activism?*

In order to nurture global citizens of the future, we need to create collaborative learning activities that strategically incorporate ongoing efforts around urgent societal challenges. As first steps in this direction, the transformative potential of inquiry-based activities is increasingly being highlighted. Despite high-level political support and well-developed practice-oriented frameworks (e.g., Next Generation Science Standards[17]), scaling these best practices to the learning spaces at large has proven a tremendous challenge. The reasons for this are diverse and complex but here we focus on one of the main factors: the conceptualization and facilitation of truly engaging and scalable inquiry-based activities remains a challenge. Activities have to carefully navigate the spectrum between being very tangible and closely mapped to the curriculum or being much broader and open-ended in nature. In the former case, projects may seem safe to the educators but risk offering very little room for students' creative exploration. In the latter case, project formulations risk turning into unstructured meta-explorations because the students lack the detailed knowledge and tools necessary to have a true, real-world impact. The combination of actual real-world knowledge creation with impact initiatives with efficient technological scaffolding may offer a pathway to a viable solution.

Increasingly comprehensive technological solutions are being developed in various domains, such as citizen science and public democracy efforts to bridge geographic, demographic and knowledge and skill related barriers (Rafner, Gajdacz, et al., 2021). For example, so-called *casual creators* use AI technologies to transform complex, skill-driven tasks into accessible and entertaining activities (Compton & Mateas, 2015): GAN-technologies can enable the general public to visualize the effect of global warming[18] and form and consider utopian and dystopian visions of the future (Rafner, Langsford, et al., 2021). However, transforming these public engagement activities into scaffolded, efficient learning opportunities for emerging global citizens presents a tremendous challenge that can only be overcome by bringing together the technology developers, civil action organizations, and active pedagogy frameworks. This endeavor should seek synergetic inspiration from the non-digital space, where efforts are underway to adapt civil action into educational activities, such as in the Community Action Guides of the Smithsonian Science for Global Goals project[19]. Here, active projects with a high degree of relevance and impact are being developed, but as these efforts scale and adapt to a global audience, increased interactive digital scaffolding will be crucial. In particular, as increasingly complex challenges are introduced in the curriculum, teachers will be faced with the challenge of supporting the collaborative exploration of all aspects of open-ended knowledge production including hypothesis formation, discussion and argumentation. Today, the scaffolding and facilitation of the open-ended exploration is largely placed in the hands of the teacher. Although first steps are being taken to support collective (citizen) scientific knowledge production and argumentation in the classroom (Rafner, Gajdacz, et al., 2021), many efforts within the interdisciplinary field of Computer-Supported Collaborative Learning (Cress et al., 2021) still need to be amplified and adapted to socio-scientific knowledge creation.

[17] https://www.nextgenscience.org/, accessed 20/2/2023
[18] https://thisclimatedoesnotexist.com/, accessed 20/2/2023
[19] https://ssec.si.edu/global-goals, accessed 20/2/2023

3.2.3 ***Challenge 2.3.*** *How to represent the learning processes?*

Once learners are collaborating with appropriately selected peers and experts around meaningful tasks, we further need technologies that create awareness of how individual and collective knowledge is built and produced, in order to support learners in developing skills such as *learning to learn* or *learning to become* (Hadwin et al., 2017). By creating models of individual and collective learning processes, we can create many types of pedagogical interventions, including visualizations, feedback, and reflective prompts. However, one of the biggest challenges in this space is to produce these theoretically-grounded data-driven models to explain how individual and group knowledge acquisition happens in complex technology-supported learning environments where learner goals and tasks to be completed may be unknown.

Prior work on pattern extraction from digital traces (Martinez et al., 2011) and expert modeling in ill-defined domains (Lynch et al., 2006) is a good starting points for this work, but these approaches have been designed for tasks where the goals and processes are within a constrained domain. Once these models are identified, another challenge will be to make the representation transparent to learners in a human-centered way to provide actionable information (Buckingham Shum et al., 2019; Dimitriadis et al., 2021). This leads to the following research perspective: How do we design human-centered (reflective) technology that models the work of students in ill-defined domains?

This initiative should engage in research on 1) what features these models should leverage, and 2) what modeling and representation techniques are best for both representing this open-ended space and creating actionable support. The research will lead to the development of AI- and NLP-based technologies, i.e., for interpreting student project work and platforms for making representations of this work visible, with the ultimate goal of improving learner awareness (Ullmann, 2015).

3.2.4 ***Challenge 2.4.*** *How to ensure development of ethical, equitable, and explainable technologies?*

Across the previous three challenges, we are proposing to develop learning technologies that are able to support each individual learner more effectively on his or her learning path. To do this, we will need to design systems of hybrid intelligence that combine different sources of human (e.g., the learner, peers, lecturers) and artificial intelligence (e.g., AI-based information technology services). The design and development of technologies is never neutral – it is imbued with the culture, values, and expectations of the people who are creating it and their local norms. This has prompted ethical concerns about bias and discrimination in how technologies are used by learners and how they are impacting their learning experiences and outcomes. In many cases, the recommendations and personalized decisions of AI technologies are not transparent or explainable, which can negatively affect their trustworthiness. Privacy concerns about what data is collected about learners, how it is used and by whom can raise further ethical issues. Prior studies have tested many ways to mitigate algorithmic and design bias in educational technologies, including co-design with diverse stakeholders, collecting diverse data for training models, using fairness constraints in training models, and evaluating how teachers and learners use technologies in diverse contexts (Baker & Hawn, 2021; Holmes et al., 2021). Others have examined ways to make algorithmic decisions explainable to users and provide transparency about what data is collected and how it is used (Khosravi et al., 2022). However, the key challenge is that technology developers and auditors cannot be expected to track the latest findings from the disparate research communities that propose solutions. Besides the normative facets that would like to be mirrored in future technologies, we know that IT systems can only leverage their potentials if they are adopted and effectively used. Consequently, we need to consider user expectations and aspects of technology acceptance during the design process to avoid user resistance or even rejection. Such initiatives will be to research and develop a set of best practices for ethical, equitable, and explainable systems, and a reliable mechanism for keeping them up-to-date (e.g., Human Computation Institute[20], (Vepřek et al., 2020). The outcome of this approach will be an evidence-based set of best practices and ideally an accessible technology that can automatically check adherence of an algorithm or an entire technology.

3.3 Theme 3: Evaluation and assessment in informal learning

Informal learning is everywhere and is life-long (Van Noy et al., 2016). The combination of formal with informal learning, both in terms of settings and learning practices, can provide substantial benefits for learners (Jagušt et al., 2018). However, this connection is made difficult by the inherent differences between the two approaches. Formal learning is institutionalized, systematic, intentional, often compulsory, prescribed curriculum, hierarchical, closed-ended and highly structured, and organized hierarchically (Callanan et al., 2011). Conversely, informal learning may be provided outside of institutions, may or may not contain teachers/instructors, may be self-directed, less structured, could be unintentional (Schugurensky, 2000). Additionally, informal learning is distinctive in being crucially linked to learners' interest and initiative, rather than resulting from demands or requirements imposed from outside. Here we single out assessment and evaluation in informal learning as one of the main obstacles for effective integration with formal learning.

The assessment and evaluation in informal learning present some unique challenges. For example, informal learning is characterized by the complexity of validating contextual, unique, interconnected, learning trajectories, as well as acquired knowledge or competencies, which have not followed a structured path. As in all forms of education, the evaluation and assessment should provide added value for the learner, which may be more important in informal settings where learners must opt into these processes. Finally, systematically taking into account informal learning that is taking place in formal settings is complex because it can occur in numerous and diverse

[20] https://humancomputation.org/, accessed 20/2/2023

physical and digital environments. We single out a challenge that focuses on some main aspect of assessment in informal learning with a goal of assuring access to pathways of learning discovery through documented learning experiences.

3.3.1 ***Challenge 3.1.*** *How to achieve equitable, fair, accessible evaluation and assessment in informal learning.*

In order to respond to this challenge, we propose looking at the issue through a lens of public participation in research, including citizen science and extreme citizen science, in order to evaluate the impact effect of recognition and self-assessment on self and others. More specifically, we propose that necessary steps would include: (1) mapping of assessment (Phillips, et al., 2018) of informal learning in public participation in research (including citizen science, extreme citizen science, citizen psyche science, fablabs, and participatory futures and relying on existing platforms such as Better Evaluation[21]) (2) constructing recommendation guidelines, best practices and (3) designing instruments for evaluating assessment, such as Open Badges[22] for external validation and granting degrees outside of formal degree programs, including the recognition of skills that are not traditionally recognized.

We believe that quick advancements can be made in this by building on the existing experiences with Open Badges, a standardized way to describe single achievements using structured data (e.g., JSON[23]). These types of badges are already being applied to citizen science[24] in foundational training[25] contexts but have not been used in extreme citizen science, or participatory futures. Thus, nuanced use of Open Badges is slightly different than the typical credentialing approach where badges in this context could be used to provide evidence of learning, the data of the badges can be used as a cohesive data set. Evidence in the badges may contain additional data, media, etc. that can also be analyzed. Open Badges can be used to develop collective intelligence models to do assessments and analysis based on such things as similar badges, skill alignments, and other metadata. It could also inform learners of the relevant and topical pathways to pursue.

Specific research to be done would start with examining the views of different stakeholders (oneself, peers, formal education institutions, employers) may have about the values of such recognition models. Based on their input, a version of Open Badges should be validated in this context by doing research on correlation of badge acquisition with knowledge/skills/competencies they signal in the informal learning in public participation in research. In addition to research,

[21] https://www.betterevaluation.org/, accessed 20/2/2023
[22] https://www.imsglobal.org/sites/default/files/Badges/OBv2p0Final/index.html, accessed 20/2/2023
[23] https://json-ld.org/, accessed 20/2/2023
[24] https://scistarter.badgr.com/public/badges/6Jg_IwmfQTaJ2kUNePsO5Q, accessed 20/2/2023
[25] https://scistarter.badgr.com/public/issuers/vWwV8z3JRHGPkKk3dMH0Wg/badges, accessed 20/2/2023

specific platform development targets would include features such as: stealth assessment in video games and e-gaming (citizen science games and digital platforms), open access validated psychometric assessments, self- and peer-assessment and badging in addition to badging by instructors or educators. By empowering learners to design and execute this evaluation process, we aim to both increase motivation and assure fairness and accessibility. Open Badges are effectively an instance of open science, a parallel to extreme citizen science, and would give the control of the evaluation and assessment process to learners themselves, including managing their own data and deciding what is available to the platform, evaluators, or future employers.

The first implementation steps of the approach would rely on a learner centered design, asking a small group of individuals to participate by keeping a diary describing what they learn as they participate in public research initiatives. This qualitative data can be thematically analyzed and formed into structured data and eventually scaled by increasing the number of learners, providing technology tools that publish the diary entries and eventually issue them as Open Badges to the students. To start with, badges can be analyzed manually, but we can envisage ways to use machine learning to provide additional insights once the amount of data increases. Much of the research for this challenge exists in the Open Badges literature (Ahn et al., 2014; Devedžić & Jovanović, 2015; Law, 2015) and the necessary development could be implemented relatively quickly.

3.4 Theme 4: Driving systemic positive change in educating citizens

Despite recent and ongoing efforts to address educational challenges, the learning ecosystem is not achieving its full potential. For example, even though the access to education and literacy among new generations almost reached 100% worldwide, there is still much to do to ensure quality education for all (SDG 4). Unequal access to inclusive educational infrastructures is still a challenge that was amplified during recent crises such as the COVID-19 pandemic. These issues are not necessarily limited by lack of potential solutions - good ideas to improve concrete education instances flourish everywhere. However, scaling-up local initiatives rarely delivers on the outcomes promised (Fullan, 2001; Tyack & Cuban, 1995). As A. Bryk (president of the Carnegie Foundation for the Advancement of Teaching) said in his 2014 AERA distinguished lecture, "as a field [education], we undervalue the importance of systematic and organized methods of learning to improve" (Bryk, 2014), attesting to our lack of capacity to learn from each other's successes and failures, leading to an increasing waste of resources (Hattie & Hamilton, 2018).

The possible causes of learning ecosystem inertia can be well described by considering it as a dynamic heterogeneous information network in which a node can be a person (learner, parent, teacher, …), a position (director of X, …), an organization (school, association,…), but also an object or a platform (Ramaciotti Morales et al., 2021). In this network, nodes influence each other's capacity in supporting, providing or accessing learning opportunities through direct or indirect influence, trust and accountability. Modeling the learning ecosystem as a dynamic network helps reveal multifarious impacts that might stem from interventions aimed at understanding systemic impacts. For example, the network effects can hamper the ability of peripheral nodes with limited social capital to access the core, creating systemic lock-in effects limiting inclusion. Given the slow renewal of "core" nodes (with access to institutional decision power), the current system shows inertia and current educational approaches aiming for beneficial change do not adapt to emerging learning opportunities, societal crises, and shifting values. This has been repeatedly demonstrated during the COVID-19 pandemic. In short, the learning ecosystem doesn't evolve at the pace of the challenges it is facing.

Another systemic effect evident in such network model are the unequal opportunities for learning generated by the lack of infrastructures (network edges) limiting inclusion. There is limited access to institutions, tech infrastructure (e.g., Internet) and opportunities (e.g., paid platforms), depending on socio-economic, geographical, psychological, barriers. Furthermore, when a learner has access, some factors impede seizing the opportunity, including basic awareness that the opportunity exists, or the fact that the voices of learners are not always heard by the people who design the system or decide how learning should happen.

Furthermore, at the system level, there is limited integration of the different components of the ecosystem, which restricts the learning pathway for learners. The resulting ecosystem is siloed and disjointed, and the learning pathway is standardized by the current evaluation system. Promising low-cost initiatives are available but face integration challenges for incorporation into standardized educational pathways. Network models of the learning ecosystems would also help assess the sustainability of potential solutions aimed at increasing learning opportunities.

One bottleneck to effecting positive change in this complex learning ecosystem is lack of agency for the learners - the learners typically do not have a mechanism for voicing problems, difficulties, and needs. Thriving systemic change in the educational system would require mechanisms to include all stakeholders' voices and values, in particular those from the learners, and ways for the system to evolve in an agile manner. We formulate these issues in two interconnected challenges.

3.4.1 ***Challenge 4.1****. How to include all kinds of learners as partners and agents of change in shaping the education system?*

3.4.2 ***Challenge 4.2****. How to create an agile learning ecosystem which is adaptive to all stakeholders' voices in the face of shifting societal challenges?*

Future citizens will face crises, unprecedented and unexpected and therefore we must build an agile and inclusive learning ecosystem. It should resemble an organic system capable of change and adaptation to new challenges in order to (1) respond to emerging learning opportunities, (2) be robust to challenges or crises, (3) adapt to shifting values, and (4) take into account the changes in the learner trajectories, e.g. learners moving across countries/continents, adopting different methods/approaches, fields. We posit that the best way to answer these challenges and achieve these goals is through participatory approaches - including all stakeholders, and in particular learners, as partners and agents of change in shaping the education system, and highlight the two interconnected challenges. We envision an ecosystem based on active inclusion and deliberation to integrate all learner voices. The actors interested in knowledge creation and practice change are best positioned to affect meaningful system change. In order to achieve true participation, relying on voice, agency and empowerment, we propose a research agenda of collective adaptation mechanisms based on its three pillars: problem identification, collective intelligence and decision making.

Firstly, in order to plan and drive systemic change, we need to map the current ecosystem to have a clear idea of what it looks like, what works where, for whom, and why, and what doesn't. Importantly, the target state is neither absolute nor locked, it can be constantly refined and adapted to an ever changing world (Galesic et al., 2022), so this requires continuous identification of existing networks, hypothesizing a set of potential desirable target network states and identifying potential trajectories leading to it. For such an adaptive framework to occur, it is key to involve the participation of all stakeholders in the mapping of the network and the curation of promising ideas for change. This requires the development and use of methods for collective intelligence in the case of education, including in particular voices from the youth. Indeed, learning pathways are as diverse as the learners.

Secondly, we need to investigate barriers to inclusion that exist today, such as representation and accessibility, and develop methods for collaborative problem solving (Greene et al., 2012) that address educational challenges while remaining agnostic/resilient to specific learner issues and solution constraints. We need to develop measures of inequalities in the system, investigate how to best include and orchestrate the voices of all learning ecosystem stakeholders as partners and agents of change. This work will be informed by numerous initiatives that explore collective intelligence practices and social participation to enact local systemic changes. The World Health Organization provides guidance to build participatory spaces that allow for meaningful dialogue and serve to amplify the voices to whom the system belongs (World Health Organization, 2021). Similarly, UNICEF elaborated a multi-country initiative that provides technical assistance to governments to implement projects that unlock the potential of data within education systems and facilitate knowledge generation (UNICEF, 2021). Along these lines, other initiatives such as the New Zealand's Kōrero Mātauranga Education Conversation and Education Summits[26] are inspirational examples of jurisdictions attempting to include all voices, namely those from indigenous communities.

Thirdly, beyond the inclusion of actors in collective intelligence processes, we need methods for collective decision making, including consensus reaching and stakeholder alignment. Unless the

[26] https://www.education.govt.nz/our-work/information-releases/issue-specific-releases/education-summit/, accessed 20/2/2023

proposed solution reflects the needs, motivations, and values of all stakeholders, it will face barriers towards adoption. These individual points of view must be taken into account in order to avoid conflict when aligning stakeholders towards making the changes needed (Biesta, 2010). Technologies that implement various deliberation methods can help foster decision making steps at scale, such as Decidim (Barandiaran et al., 2018) and Teachers as Researchers (Pagnotta et al., 2022). Moreover, local infrastructures operating as middlegrounds can act as network hubs connecting upper (institutions) and underground and foster smaller scale events connecting stakeholder representatives to promote embodied meetings to foster alignment (Irrmann, 2022).

Finally, we need to explore how systemic network effects can lead to compounding inequalities in the ecosystem. For example, preferential attachment can lead to the centralization of the network towards overly influential hubs (rich-get-richer phenomenon), limiting the ability for novel nodes in the system to access resources (Santolini et al., 2017). Similarly, homophily (the tendency to connect to nodes that are similar to oneself) can impede diversity in the network, limiting access to a balanced set of stakeholders in one's ego-network. As such, we need to understand what processes elicit the mitigation of these undesired outcomes *by design*, thereby minimizing the need for interventional approaches.

Problems faced by learners operate at different scales: that of the classroom, the school, the district, the state, as well as the usage of particular edtech tools. As such, we consider that participation and inclusion need to be fractal so that learners can be partners and agents of change in shaping the education system at all levels of complexity. The path to solution will of course not be instant, and the proposed initiatives rely on two parallel threads that operate at different timescales. On the one hand, the elaboration of proofs of concept at the level of select pioneer communities will allow the development and implementation of monitoring and evaluation frameworks within 3-5 years. For example, the case of a massively collaborative problem solving techno-social platform (Greene et al., 2012) can be deployed within a 5-year time-frame with incremental capability and scale, and an initial minimum viable platform by the end of year one to enable iterative development based on feedback and impacts. As a platform that runs constantly, it could be used in an ongoing manner to aggregate new learner issues, crowdsource candidate goals, and build solution paths. While the problem/resolution process is necessarily ongoing, due to shifting contexts and emerging awareness, the enactment of solutions could be either discrete policy decisions, or ongoing process-based solutions or combinations of both. The generated insights can then feed proposals for wider implementation and refinement at the institutional levels on longer time-scales (10-15 years) that will consolidate the proofs of concepts, fundamental and applied research to enhance collective participation, intelligence and adaptation in education.

The proposed initiative is situated within use-inspired basic research. At the theoretical level, it tackles questions related to processes of network formation, the development of systemic biases hampering inclusion, processes of deliberation, incentivization, and collective decision making. In parallel, it leverages an agile experimental methodology, prototyping proof-of-concepts within ongoing communities such as Teachers As Researchers (Pagnotta et al., 2022), with the aim to implement solutions at scale to the different layers of the education system. The proposed solution is by design participatory, thus positioning empirical insights as the core source of data and analytical processes. It iteratively feeds pilot data and ultimately real-world deployment data back to refine and improve the approach as driven by learner-led outcomes.

4. DISCUSSION & CONCLUSIONS

In this position article we have described the methodology and outcome of a workshop - a collective intelligence experiment carried out at the Learning Planet Institute in collaboration with several researchers, experts, practitioners of the domain. Through the protocol described and the activities held during the workshop, we have outlined and mapped promising paths for the development of the future of this emergent field, connecting collective intelligence with learning.

A first overarching issue present across all of our identified themes, is that of the need for development as much the need for research and the necessary interplay between the two. So far, collective intelligence and learning have remained research endeavors, and despite the arguments accumulating that show their importance in tackling large-scale systemic change, no comparable effort has yet emerged in development. Accordingly, one of the main points raised in this collective document is that of the challenges to be overcome in moving forward the discipline towards impact beyond research communities, into policy, governance, communities, technologies, and practice in general.

A second line of ideas consistently identified in all proposed themes, is that of alignment: much as collective intelligence and learning are, as phenomena, related to alignment, the future of the discipline must also be structured, when possible, with positive societal outcomes. While difficult to define, we have discussed at great length about how the state of this field may be aligned with societal objectives. One of the main results of our exercise is the collective view under which the development of the field, because of the projected impacts in large social and technical systems holding great risk but also great promise, cannot be disentangled from clear definitions of positive societal outcomes. In our view, activity in collective intelligence and large-scale learning, be it on research or in development of applications, must seek constant dialogue with the communities that define, govern, and promote these outcomes. A comprehensive outline of all the values underlying these outcomes and a systematic comparison with existing examples throughout the world is beyond the scope of our work here. However, we do stress the importance of co-creation of these elements among members of the field and those of the broader community.

A third dimension of our results that pertains to all proposed themes is that of engagement, which relates to previously mentioned importance of co-creation of values for alignment. For the field to thrive and for applications to harness the potential outlined throughout this document, diverse forms of participation are required. The vision stemming from our definitions, and supported by the literature review we provide to sustain our collective proposal, is one where engagement must be included by design in the process, and to be expected as an outcome success. The most prominent form of engagement identified is through the continuous formation of learners at different levels and –most importantly and often understated– across stages of their careers. Collective intelligence and learning research and development efforts must include this feature by design. In practice, as we discuss at different stages of this document, this involves linking efforts, projects, interests, and communities that would seem otherwise scattered.

Our hope is that the potential of collective intelligence and learning, identified as a one of the key transformational drivers in several societal and industrial domains, may profit from this seminal moment to set the bases of the alignment that is needed to assure positive outcomes. It is in line with this hope that we offer the results of our collective experiment on the future of collective intelligence and learning. Much care was put in transversality across different dimensions intersecting this field. No doubt, however, the technical and social substrate that inspires our proposal is bound to evolve. It is maybe by the very ever-transforming nature of collective phenomena that we are acutely aware of the limitations of our exercise and our results. Sustainable strategies for advancing the themes proposed here cannot overlook this essential limitation, and we thus submit to the broader community this document as an artifact not only of our experiment and its results, but as a living document that is welcoming future open contributions.

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DM designed and organized the workshop. JR, OP, IA, PRM, and MS co-organized the workshop. Writing of the specific sections was led by the following authors: DM &VH (Introduction), DM (Methods), JMS (Theme 1), IN (Theme 2), OI (Theme 3), IA (Theme 4), PRM (Discussion).
All coauthors participated in the workshop discussions, wrote elements for the initial paper draft, reviewed and edited the manuscript. The author order is alphabetical, with the exception of DM, who is the first and the corresponding author.

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