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AI as an accelerator for defining new problems that transcends boundaries

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Abstract

Interdisciplinary, transdisciplinary, convergence, and No-Boundary Thinking (NBT) research are methodology and technology-agnostic approaches to problem solving. The focus is on defining problems informed by access to multiple knowledge sources and expert perspectives across different domains, with the goal of accessing all available knowledge sources and perspectives. While access to all available knowledge sources and perspectives could be seen as a difficult to attain objective, with the recent rise of AI we might be closer to approaching this goal. We review several examples of methodologies and technologies that have been used to put these strategies into action, but the primary focus of this paper is on how recent advances in AI now enable a quantum leap forward in *defining new problems*. By leveraging the capacity of AI to synthesize knowledge from multiple domains, these tools can be used to propose multiple candidate problem definitions. AI is uniquely able to draw upon many more knowledge sources than any individual-or even a very large team-could. Coupled with human intelligence, better problems can be defined to address complex scholarly or societal challenges.

Keywords: No-Boundary thinking, Convergence, Artificial intelligence, Problem definition, Interdisciplinary science, Team science

Introduction

Science has rapidly advanced over the past few decades, but with this advancement comes the realization that many remaining and emerging problems are increasingly complex and wicked [1]. For example, consider the complexity of addressing challenges such as worldwide climate collapse, global economic development in the context of sustainability, and global healthcare for a growing and aging population. Solutions to these challenges require defining new problems that can be realistically addressed. The definition of these new problems can only come about through an approach that engages teams of researchers possessing diverse perspectives, so that all important aspects of the problem are captured in its definition. The path to effectively dealing with these problems starts with reframing their problem definition. Defining these problems rarely can be done through a single disciplinary perspective by an individual researcher. Interdisciplinary science, convergence science, team science, systems thinking, NBT and other theories and methodologies have all emerged as viable strategies for addressing increasingly complex problems. Disciplinary science seldom is sophisticated enough to deal with higher-level problems that emerge when complex systems get out of balance. The theories and methodologies listed above are all attempts to take a higher-level perspective by including those with different perspectives and approaches.

Recent advances in artificial intelligence (AI) now permit it to help in properly defining a problem by tapping into more knowledge sources and perspectives than a single individual could ever bring to bear. *Note that we are referring to assisting in the **problem definition** phase and not its traditional use in the **problem solution** phase.* Our hypothesis is that more relevant problem definitions can be created by considering all knowledge sources and perspectives that can tease out the interplay among interacting factors, anticipate issues that might arise, and propose possible avenues to investigate. AI has recently emerged as a game-changing assistant for these approaches. Solving complex problems requires many different perspectives, as a result, researchers seek to expand their knowledge sources by configuring their teams to harness and integrate diverse expertise from different disciplines. Thus, the scientific community has become much more open to the concept of interdisciplinary teams convening to solve complex problems and defining the problems together, moving beyond a model of disciplinary scientists each applying their skills and passing their contributions on to the next group of scholars. Yet, even a diverse, interdisciplinary team may need to reach beyond their collective expertise and domain knowledge to converge on a solution to the problem they are attempting to solve [2, 3].

This paper focuses on the importance of being able to access many knowledge sources in the Problem Definition phase. We demonstrate the use of AI as a tool to tap into a vast amount of knowledge, integrating and synthesizing these sources for defining new problems that can provide solutions for the very complex scientific and societal problems that we face. The remainder of this paper is organized as follows. First, to provide context for our thesis, we begin by framing interdisciplinary, convergent, team science, and NBT relative to the modern scientific method. We then review several projects that have recently been undertaken in a manner that is consistent with recent efforts toward interdisciplinary research. We also provide a brief overview of technologies in place to enhance these strategies, focusing primarily on AI and related intelligent technologies, with a couple of examples. We then discuss how these theories and methodologies can be enabled by AI and the future of such approaches.

Framing the scientific method

Ever since Francis Bacon in 1620 first proposed the modern scientific method in his Novum Organum [4], researchers have been trying to improve upon its basic philosophical reliance on reduction and inductive reasoning centered upon experimental research. Bacon's approach enabled the development of a variety of methodologies over the centuries that have capitalized upon rapid technological advancements. While we have been bumping into the limitations of disciplinary science, it has been a useful and necessary approach for managing the sheer volume of information arising from the Age of Reason. Bacon believed that discovering "new unshakable truths about nature... is not the work of single minds but that of whole generations by gradual degrees toward reliable knowledge" [4].

One way of illustrating the modern scientific method is shown in Fig. 1. Though the figure depicts two phases, Problem Definition and Problem Solution (we'll figuratively refer to these as the Thinking and Solving phases, respectively), it is commonly accepted that there is a lot of interaction between these two phases, hence the arrows between the two larger boxes. Nested within each of these two larger boxes are a couple of components with their own feedback loops: Idea Generation and Hypothesis Creation within Problem Definition, and Investigation and Evaluation within Problem Solution.

Addressing complex and wicked societal problems necessitates identifying the appropriate questions and carefully defining the right problems to investigate [5, 6]. According to Gajary et. al. [5], coming up with a well-defined, researchable problem formulation is a creative process that generally emerges organically from the knowledge vision at the start of any research project. Problem formulation is the act of turning a research question into a solvable problem. This process is subject to all the successes and failures one encounters in addressing complex problems [7]. Each phase, theoretically, draws upon an infinite source of inputs: all potential knowledge and all potential perspectives in the Problem Definition phase, and all potential resources, tools, and skills in the Problem Solution phase. In practice, to manage information volume and performance issues, there is a filtering process [8] that prevents us from drawing infinite inputs from these sources. We have labeled these filters the T-Filter and the S-Filter (for Thinking and Solving, respectively) in Fig. 2.

A T-Filter limits our full access to the **Knowledge+Perspectives** cloud because:

- The knowledge we need might not have been generated yet by our civilization.
- The research team's breadth and depth of knowledge might be too limited.
- The research team's perspectives might be too limited and/or culturally biased.
- There is too much information, so it is impossible to consider all of it.

An S-Filter limits our full access to the **Resources+Tools+Skills** cloud, because:

- Funding is determined by grant-writing ability and societal priorities.
- The research is limited by the availability of skilled technicians.
- The technology might not have advanced sufficiently to meet our needs or ability to process all the pertinent information.
- The research team lacks adequate training and skill in working with others from other disciplines and perspectives.

While there will always be blockages to information and resources due to these filters, efforts to improve the scientific method are continuously trying to widen the gaps between these blockages to allow more access to these clouds of capability. Our stance in this paper is that AI can serve as accelerator agent to widen the gaps in much more significant ways than we have been able to in the past. To set the context, we briefly review other recent efforts (outside of AI) to improve the scientific method.

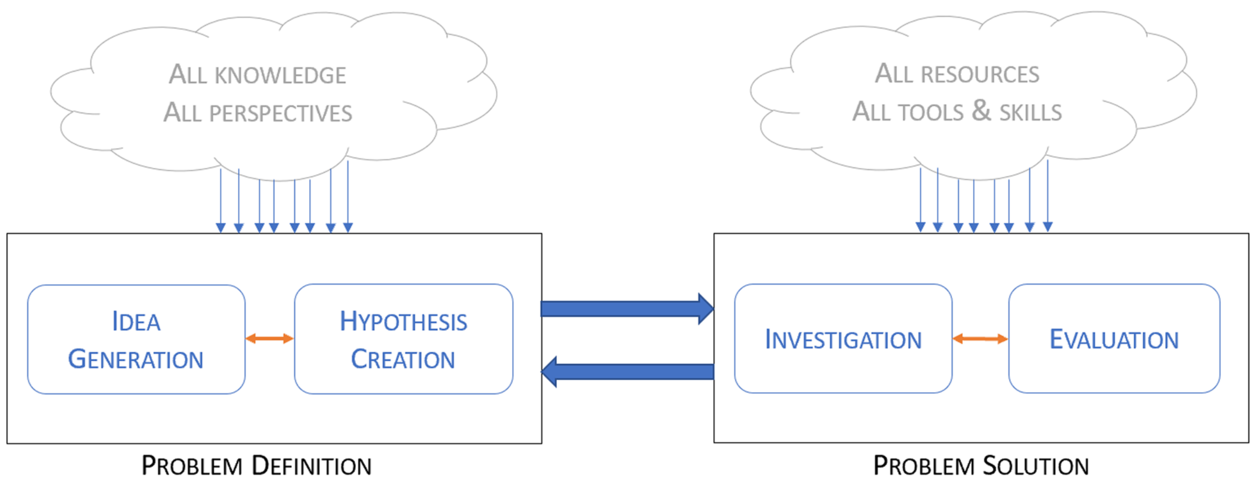

Fig. 1 An illustration of the modern scientific method highlighting the two key phases of problem definition and problem solution

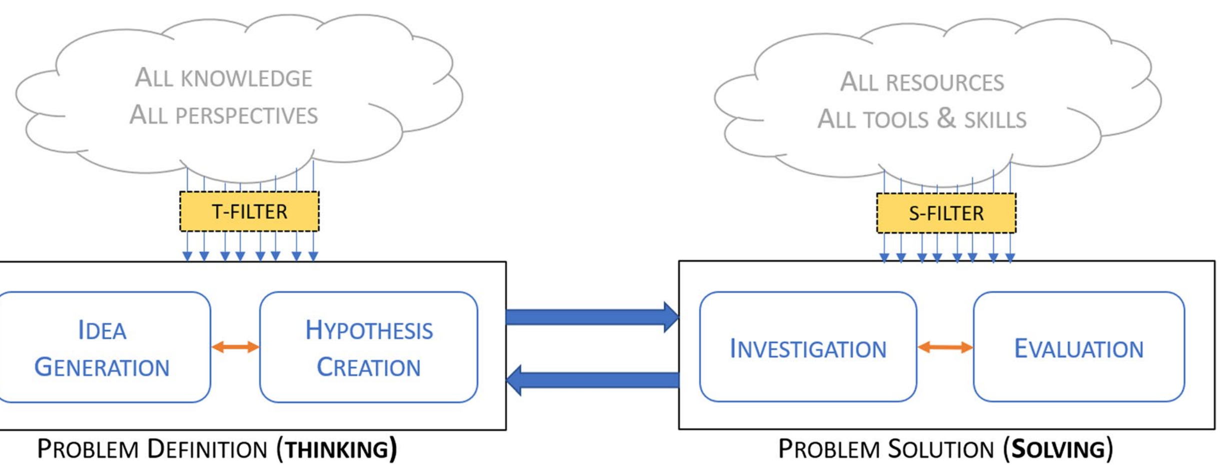

Fig. 2 Modifying the scientific method illustration to depict the thinking and solving filters

Modern methodologies for enhancing the scientific method compatible with interdisciplinary goals

This section provides a brief overview of a few methodological enhancements to conducting scientific research that most readers will have encountered over recent years. While far from an exhaustive, each in its own way has tried to reduce the amount of ”T-filtering” that occurs in the Problem Definition phase illustrated in Fig. 2. By providing greater access to additional knowledge sources and supplementary perspectives, each method aids in the problem-defining process.

No-Boundary Thinking (NBT)

A model of joint inquiry and scientific investigation to addressing complex problems has been long advocated by a small group of resolute bioinformatics researchers who coined the term “No-Boundary thinking” (NBT) [9, 10] as a strategy for approaching complex scientific problems. NBT advocates for early-stage problem definition but also taking an agile and long-term perspective to the evolution of problems as they continuously unfold over time with newly arriving information. NBT inherently adapts to new insights and shifting challenges. Its approach builds upon complementary efforts that have had similar goals, yet adds new perspectives gained by collective experience in trying to deal with complex problems using interdisciplinary approaches. No-Boundary Thinking is a discipline agnostic approach for scientific discovery and education that accesses, integrates, and synthesizes data, information, and knowledge from multiple and evolving perspectives to define important problems leading to innovative and significant questions that can subsequently be addressed by individuals or collaborative teams with diverse expertise [10].

NBT is a paradigm shift that asks us to take a broad, appropriate perspective in solving real problems by focusing on properly defining new problems [9]. Yet, the very process of defining a problem and its potential solution includes placing boundaries around what can be accomplished in a reasonable amount of time and with limited resources. Even the process of putting a problem definition into words brings with it the cultural boundaries and the modes of thinking embedded within the chosen language. According to Jiddu Krishnamurti, “If we can really understand the problem, the answer will come out of it, because the answer is not separate from the problem” [11]. By defining a problem too narrowly, we limit the applicability of any solution we may find. By asking the right question, we are much more likely to generate a solution that meets real needs. At the very core, NBT is an abstract ideal concept that makes it very challenging for researchers to figure out how to put it into practice. However, carefully defining new research problems is the key to making scientific breakthroughs, solving wicked problems, and really making a difference. While the process of defining a specific problem necessitates dropping boundaries around what can be accomplished, an NBT approach compels us to continually redefine our research problems with possibly fluctuating boundaries within a long-term perspective[1].

[1] There is also the informal concept of type III error in statistics that happens when you ask the wrong question. This is derived from the formal concepts of type I and type II errors.

NBT is discipline-agnostic. It transcends all methodologies and approaches, as well as all technologies, and yet draws upon them all when appropriate. NBT goes beyond merely integrating multiple disciplines; it integrates and synthesizes multiple knowledge sources including, for example, subject-matter experts, the collective wisdom of groups, end users, and data, information, and knowledge repositories. There have been many methodologies that have made valuable contributions to NBT including interdisciplinary science, convergence science, team science, systems thinking, etc. Likewise, there have been many technologies that have contributed to taking a broader approach to problem definition, including "big data", federated databases, AI and machine learning (the focus of this paper), etc. While NBT is technology-agnostic, AI is uniquely able to draw upon many more knowledge sources than any individual-or even a very large team-could. Combined with human creativity, access to these many knowledge sources enables definition of new research problems. Yet, it isn't enough to just have access to all knowledge; the knowledge needs to be connected and new ideas from that knowledge synthesized to define a problem.

Team science

One of the defining characteristics of a successful project is the engagement of all team members in early-stage problem definition to promote the synthesis of ideas and approaches from available knowledge. The composition of the team must reflect the diverse expertise, experience, and backgrounds needed to properly define the problem. We have previously proposed that it can be useful to consider where the usual boundaries reside [12]. Apart from the obvious disciplinary boundaries, communication among team members can often pose a challenge to project success, which makes developing a shared terminology amongst team members a priority [13, 14]. Bezrukova et al. [15] describe "faultlines" that exist within interdisciplinary teams, which can occur in teams with diverse composition in gender, age, ethnicity, etc. A classic example of this is the challenge of biologists and computer scientists speaking different disciplinary languages that can limit the effectiveness of collaboration.

The advantages of forming diverse teams are highlighted in [16, 17]. A key observation reported is that team members from a variety of diverse backgrounds seem likely to have experiences that enhance traits leading to success in innovative science, including risk taking, perseverance, and communication skills. It has also been shown that gender-diverse teams can generate more novel and impactful scientific results [18]. Including team members with not only diverse disciplinary backgrounds, but also multiple diverse cultural, racial, gender, age, disability, and other backgrounds can lead to success through viewing problems from many perspectives. To transcend these boundaries, it is important to address some questions about team composition and function at the beginning of the project, including how to identify the diverse group of experts to contribute to problem definition, how to facilitate effective communication, and how to form the solid interpersonal relationships necessary to avoid triggering the underlying faultlines. Developing evidence-based techniques for giving everyone a voice, defining a shared vocabulary, and training team members in key interpersonal skills play an important role in effective team science.

Interdisciplinary science

The interdisciplinary team approach to research brings together experts from diverse academic disciplines to collaboratively address complex research problems [19]. The core tenet is that integrating knowledge and methods from various fields can lead to more comprehensive and innovative solutions than any single discipline alone could achieve. Scholars in the social sciences have noted that interdisciplinary groups are better at solving deep and difficult scientific problems [20]. This approach can also be regarded as multi-disciplinary or trans-disciplinary though the differences between them are minor. According to Choi and Pak [21], multidisciplinarity draws on knowledge from different disciplines but stays within their boundaries while interdisciplinarity analyzes, synthesizes and harmonizes links between disciplines into a coordinated and coherent whole. Transdisciplinarity integrates, for example, the natural, social and health sciences in a humanities context, and transcends their traditional boundaries. Whether inter- or multi- or trans- disciplinary, there is a shared belief that overlaps with the NBT and convergence (See next section on convergene) approaches: they foster creativity and innovation by removing the "boundaries" of conventional thought processes. However, NBT and convergence science go beyond merely integrating multiple disciplines. They seek to redefine how we approach science by emphasizing the underlying motivation to solve problems, particularly during the *Problem Definition* phase as well as a holistic view of knowledge and problem-solving.

Scientific discovery is an agile and spiral process that acknowledges that problems are continuously redefined as more information and knowledge become available. Unlike an interdisciplinary approach, which often requires the careful integration of distinct disciplines [22], more modern approaches promote a fluid blending of ideas and methods at an early stage, as well as throughout the problem-solving process. This reduces the complexities and challenges of coordinating multiple, distinct academic frameworks. NBT and convergence research, for example, encourage deep understanding through the exploration of connections and patterns that transcend traditional academic boundaries [23]. The interdisciplinary team approach confines learning to specific disciplines [24], while here we encourage a more natural exploration of all available knowledge from every discipline. This can be less overwhelming for learners, allowing them to follow their curiosity and intuition, leading to a more organic and less confusing learning experience. This approach can also be less resource-intensive than a full interdisciplinary strategy, as it does not require experts from every relevant discipline but rather leans on the ability of individuals to adopt a more holistic, flexible mindset.

Convergence research

Over the past decade, convergence research [2, 5] has become a high priority for addressing complex problems in science, engineering, and society, as highlighted by the National Science Foundation [3]. Convergence is an approach to problem solving that integrates expertise from multiple sciences, including the biological, physical, mathematical, and computational sciences, medicine, and engineering to form comprehensive synthetic frameworks that merge areas of knowledge from multiple fields to address specific challenges. Convergence builds on fundamental progress made within individual disciplines but represents a way of thinking about the process of research and the types of strategies that enable it as emerging scientific and societal challenges cut across disciplinary boundaries in these fields. The concept of convergence is meant to capture two dimensions [25, 26]: (i) convergence of the subsets of expertise necessary to address a set of research problems, and (ii) formation of the web of partnerships involved in supporting such scientific investigations and enabling the resulting advances to be translated into new forms of innovation and new products.

Convergence research shares common characteristics with interdisciplinary methodologies that are widely applied in fields like health, engineering, and technology, where multidisciplinary teams collaborate.

Systems thinking

No-Boundary, interdisciplinary, and convergent research requires that teammates with different training and perspectives work together throughout the problem definition and solving process. The systems thinking community has identified practices that support the solution of problems that involve multiple systems by thinking of them as an interconnected whole and not breaking the problem down into various parts. According to the Waters Center for Systems Thinking [27], systems thinking "encompass[es] a spectrum of strategies that foster problem-solving and encourage questioning". The following characteristics of systems thinkers are also helpful to interdisciplinary teams.

Systems thinkers learn to make meaningful connections within and between systems. An example is attention to common definitions and cognitive approaches for constructing the artifacts needed to articulate, understand, and communicate problems, solutions, and results [28]. Systems thinkers seek to understand the Big Picture, not just one cultural or disciplinary perspective. They understand how things may change over time and learn to adjust their understanding of the problem in the context of a changing environment. These are essential elements of both the scientific method and No-Boundary Thinking. Systems thinkers know how to surface and test assumptions about a particular problem that addresses multiple systems as a whole; No-Boundary thinkers need to surface and test assumptions from diverse perspectives. Especially important is the ability to design out-of-the-box problems and solutions after listening to and understanding multiple views from a diverse team of thinkers. Systems thinkers understand that a system's structure generates its behavior. Systems thinkers resist the urge to quickly come to a problem definition and solution. This is especially important because it takes time to hear, explore, and integrate multiple perspectives. Systems thinkers pay special attention to checking results and changing the problem definition and solution strategies when and where needed. Systems thinking moves science beyond reductionist approaches which were originally developed to manage overwhelming amounts of information.

Beyond the above approaches

A central argument of this paper is that, in this era of AI, we are once again able to focus on the broader picture, thanks to databases and analytical tools that *help* facilitate analysis, even amidst an overwhelming influx of diverse data. The term "facilitate" is significant, as human intelligence in the loop remains essential to bridge gaps across disciplines and interpret the insights generated by the advanced computational tools.

These approaches to problem solving aim to go beyond merely integrating multiple disciplines; they intend to integrate and synthesize multiple knowledge sources including, for example, subject-matter experts, the collective wisdom of groups, end users, and data, information, and knowledge repositories. While as described above, there have been many methodologies that have made valuable contributions to these goals, there have been many technologies that have contributed to taking a broader approach to problem definition, including "big data", federated databases, AI and machine learning (the focus of this paper), etc. While the above approaches are technology-agnostic, AI is uniquely able to draw upon many more knowledge sources than any individual--or even a very large team--could. Combined with human creativity, access to these many knowledge sources enables definition of new research problems. Yet, it isn't enough to just have access to all knowledge; the knowledge needs to be connected and new ideas from that knowledge synthesized to define a problem. As we have pointed out before, most problems today do not fall within reductionist silos, and a major point of this paper is that in this era of AI, we can again look at the bigger picture because we have databases and analytical tools that can assist us even when there is a flood of different kinds of data. This word "assist" is important, as we still need human intelligence in the loop to bridge the gaps among the disciplines and make sense of the responses that our intelligent computational tools provide.

Applying interdisciplinary research in action with compatible methodologies

The following examples demonstrate the application of interdisciplinary methodologies to the problem definition process. Each example highlights a different aspect of the scientific methodologies described earlier in this section. It is important to note that no example fully encapsulates the ideal concept, as it signifies a philosophical or utopian ideal that continues to evolve with the advancement of knowledge and passage of time.

Behavioral model of pedestrian dynamics under emergency and non-emergency scenarios using cellular automata

The project was carried out by a team of researchers from the University of Rhode Island in partnership with a scholar from the Disaster Research Center at the University of Delaware (NSF Award Number: 0331984). This example of interdisciplinary research in action underscores the essential role of team science in the problem definition process of investigating evacuation of pedestrians from buildings during unforeseen disasters [28].

The research work was inspired by the emergency incident that occurred on February 20, 2003, in Rhode Island, which resulted in the deaths of 100 individuals and injuries to 230 others, as well as the September 11, 2001, attacks on the World Trade Center in New York. The objective was to gain a deeper understanding of how individuals and groups navigate buildings during emergencies, enabling architectural experts and safety personnel to develop environments and protocols that facilitate safe and efficient evacuations. The problem can be classified as wicked, as there no straightforward articulation and is impossible to solve in a way that is simple or final[2]. Human behavior is very complex,

[2] https://www.stonybrook.edu/commcms/wicked-problem/about/What-is-a-wicked-problem

especially given that multiple structural, situational, social, and psychological factors impact actions during emergency situations.

The principal investigator, a transportation engineering scholar, convened the interdisciplinary team to augment their expertise on the flow of automobile traffic on highways. This included a computer scientist with expertise in computer graphics and visualizations, a social psychologist with expertise in understanding group behaviors during disasters, a psychologist expert in understanding individual behaviors, and a computer scientist with cognitive modeling expertise to assist with team communication and enhance the team problem definition process. The team also consisted of other key domain representatives such as a first responder, an evacuation equipment industry partner, and airport terminal director. Students from engineering, computer science, and the social sciences were also part of the team. Given lapses in evacuation readiness were present in many building evacuation situations, the team collectively formulated the research problem: the development of a simulation tool to effectively support understanding of the behaviors of people during evacuations from buildings during emergencies to ensure adequate preparations. The entire team was engaged during the problem formulation process, thereby supporting the important principle of having diverse perspectives present throughout the whole process from beginning to end.

Initially the team experienced the usual communication issues of most interdisciplinary groups: terminology across the disciplines, taste in problem formulation, differing constructs and diagrams used to support the expression of problems and solution, etc. Special attention was paid to developing a common means of expressing and documenting the aspects of the problem [29]. The modeling expert worked with the team to develop a constructive means for everyone to define artifacts to convey their contributions. In line with team science, this highlighted the importance of a shared set of constructs, language, and artifacts to support team discussions about the problem formulation and solution and provided a well understood and domain agnostic language for disseminating the results of the project more broadly. Together, they determined how each disciplinary perspective would be appropriately embedded in the problem and solution.

When this project was carried out, AI and machine learning had been developed by computer scientists but had not yet been widely adopted and applied to other disciplines. Problem refinement was done by the whole team, as was necessary in the absence of intelligent computational aids. That is, the thinking and solving filters were already applied before the problem was fully formulated and solved, by virtue of team selection. Later in this paper, we discuss a process that supports the discovery and definition of problems using intelligent computational tools that are currently available and able to pull information from broader and larger sets of data, and show promise to support problem discovery and definition That is, the most robust interdisciplinary team might typically include multiple human perspectives, and an intelligent computational data and information analyst to broaden access to more information than could be reasonably be consulted by humans alone, thus partially eliminating the thinking and solving filters. The team manually chose the set of expertise and perspectives that they thought was appropriate and solved the problem using the analytical tools present in and familiar to those domains.

Examination of multi-tier supply chains: network metrics of ICT multi-tier suppliers and buyer financial performance

This example also illustrates interdisciplinary science in the thinking phase of a project via the integration of several domains to address complex research problems. The project was conducted by researchers from the College of Business at the University of Rhode Island to investigate the role of lower-tier suppliers from the information and communication technology (ICT) industry and the impacts of their network metrics on buying firms' financial performance. Participants came from diverse academic disciplines, including supply chain, information technology, finance, statistics, data analytics, etc. Such a complex problem-defining process produced a blend of research ideas and analysis methodologies to define and solve the supply chain issues at the early stage of the project. The issue of how lower-tier suppliers (e.g., tier-2 suppliers) are engaged in buying firms' multi-tier supply networks and improving those buying firms' performance remains a substantive research issue that motivated the study.

To identify the association between lower-tier suppliers and buyer performance, the researchers narrowed it down to "digitally enabled multi-tier supply chains", which means buying firms' collaboration with suppliers is more driven by technological parts and components across the entire scope of supply chains and extends to lower-tier suppliers [30, 31]. The digitally enabled multi-tier supply chain might be different from those in other industries regarding the lack of physical processes of parts and components, such as inventory, warehousing, and shipping from suppliers [32, 33]. Considering the growing number of ICT suppliers in the US, an issue was discussed about buying firms' identification and connections with suppliers, including lower-tier suppliers. For example, *Microsoft* provides components and services to buying firms through tier-1 suppliers. Those buying firms, such as *Ford*, need to decide how to receive support from multiple suppliers. Thus, the research project is further specifically motivated to observe both tier-1 and tier-2 suppliers and how they are associated with buying firms' performance in digitally enabled multi-tier supply networks.

The team framed their interdisciplinary exploration of supply chain, information technology, and network analysis, utilizing multiple analytical methodologies and generating an interdisciplinary research question: *Do network centrality metrics of multi-layer suppliers affect buying firms' financial performance in multi-tier supply chains, by including lower-tier suppliers from the ICT industry?* With the aid of relevant theoretical and empirical research methodologies, they were able to formulate the conceptual framework and hypotheses and iteratively decide on the optimal problem-solving approach to move from the thinking into the solving phase.

Stress-related disorders

Application of systems thinking to aid problem definition, has resulted in a better understanding of the bigger picture in biomedical research by enabling researchers to pull together knowledge about organisms, tissues, and cells [34]. This is demonstrated through another related example conducted by a team at UT Texas on a stress-related disorder project. Their project sheds light on the differences occurring in the brains of people with post-traumatic stress disorder (PTSD) and depression compared to neurotypical controls [35]. The team's objective was to uncover how stress related disorders arise from the interplay between genetic susceptibility and stress exposure [36]. They combined circuit biology with powerful multiomics tools to delve into the molecular pathology behind these disorders [35]. The research combined transcriptomic, methylomic, and proteomic data to describe the status of the brain in individuals with PTSD and major depressive disorder thus not only combining different biological models, but also including the psychological information/diagnoses.

Modern technologies for enhancing the scientific method

Rapid advancement of technologies has enhanced scientific research in diverse ways [37]. In fact, much scientific progress has been based on advances in technology that allow for increasingly accurate measurement of physical phenomenon. However, when one considers the use of technology in scientific research, it becomes apparent that technology has been primarily applied in the *Problem Solution* phase (or *Solving* phase; see Fig. 1) and not necessarily in the *Problem Definition* phase (or *Thinking* phase). Since multiple perspectives are usually brought to bear on problems once defined, we divulge further on how technology might be useful in defining problems.

The primary applications of technology in the *Thinking* phase are: (a) supporting the creation of relevant and accessible knowledge sources, and (b) enabling the efficient exploration of these knowledge sources. The goal is to apply the technology to reduce the amount of T-filtering that occurs in the *Problem Definition* phase illustrated in Fig. 2. By providing greater access to additional knowledge sources and supplementary perspectives, technology can be harnessed to enhance the problem-defining process.

Technologies for creating knowledge sources

The examples of using technology to create knowledge sources are too numerous to list exhaustively. Rather, we present two prominent modern examples: Big Data and Data Federation. Even though the term "big data" has been around since the 1990s [38], the technology advancements required to address the use of all available data remains elusive and cost-prohibitive for many even for the largest tech companies, governments, and large international collaborations [39]. One of most widely known big data projects in the bioinformatics area has been The Cancer Genome Atlas (TCGA) Program [40]. While not without criticism [41], the underlying goal of this project was to develop searchable data sets that would support discovering new insights into cancer biology [42]. Within the scientific framework described previously, the Computational Genome Analysis Platform (CGAP) enhanced the ability of researchers to more easily access the knowledge collated and to pull it through the T-Filter in the *Problem Definition* phase.

Data federation and data virtualization wrap multiple data repositories into what appears to be a single system [43]. The individual repositories can have different provenances, be in different formats, and be physically dispersed. In effect, this pulls in additional knowledge sources through the T-Filter to be used in the *Problem Definition* phase by providing access to multiple data sources in a (mostly) seamless fashion.

Technologies for exploring knowledge sources

All of us have likely utilized a range of technologies to explore various knowledge sources, including browsers, search engines, statistical analysis tools, visualization platforms like virtual and augmented reality, as well as knowledge management and relationship management tools. All of these are useful and appropriate in a variety of contexts, yet most are focused on one (or a few) users interacting with a specific knowledge source and thus are limited in scope.

While not denigrating the above applications of technology to explore knowledge sources, we believe that recent advances in AI are particularly suited to accelerating the Problem Definition phase. We postulate that AI can be a powerful assistant in supporting Problem Definition approach because of its ability to efficiently collate and analyze large volumes of information. In the future, new technologies certainly will provide even more capability in accessing and analyzing even better and expanded knowledge sources. However, in this work, we now focus on how AI can be utilized as an accelerator agent to enhance Problem Defining.

Using AI to enhance problem definition

Recent advances in AI, and in Large-Language Models (LLMs) in particular, have astounded the research community [44]. Significant applications of large AI models in health informatics include medical image analysis, natural language processing and predictive analytics. LLMs are pre-trained on language data and applied to domain downstream tasks [45]. While there are many valid concerns about how to use these technologies appropriately, the ability to draw upon so many knowledge sources and multiple perspectives using AI enables a quantum leap forward in being able to define relevant problems since increasing a team's size isn't always the answer to gain access to more sources and perspectives and inefficiencies in communication can become dominant [46]. *While human creativity will always be required in the Problem Definition phase, AI allows access to a many-orders-of-magnitude greater number of sources and perspectives than could be possible through the efforts of an individual researcher or even a large team of researchers and their support staff.* Idea Generation and Hypothesis Creation (See Figs. 1 and 2) require a different kind of intelligence than computational models can provide, yet the appropriate use of AI in the Thinking phase enables better problem defining.

We recognize the tremendous amount of work that needs to take place to make these knowledge sources and multiple perspectives accessible and useful to an AI (common ontologies, intelligent tools for aligning ontologies and knowledge graphs, ethical use of data sources, etc.), but still believe that the benefits of this work, including enhanced productivity in the Problem Definition phase, will far outweigh the costs. AI presents us with an opportunity to greatly reduce the T-Filtering that occurs in the Problem Definition phase, in a sense opening some of the bottlenecks in the T-Filter. Human creativity will always be important in defining a problem. Millions of years of evolution has created a human brain that is capable of sifting through vast amounts of information and identifying the salient aspects. AI is a different kind of intelligence that can sift more efficiently through larger quantities of information finding commonalities and making connections, but the human brain is needed to help determine which of these connections are relevant. Human creativity plus AI makes a powerful combination in identifying interesting and relevant problems.

Research with diverse teams in action with modern technologies

This subsection illustrates a few examples of applying interdisciplinary compatible methodologies to the problem-defining process.

Climate change query system

In [47], an LLM is designed to generate responses to queries about climate change from various interdisciplinary perspectives. These perspectives include Economics, Natural and Environmental Science, Social Science, and a general overview encompassing all three disciplines. The team collaborated to create a diverse set of prompts and completions that covered a wide range of climate change topics from different disciplines. This ensured that the model was trained on a comprehensive and interdisciplinary set of data. AI and LLMs were used to integrate the interdisciplinary knowledge and ideas of the team into the ClimateGPT models.

Alzheimer's disease knowledge integration

In this example, we demonstrate the process of AI in accelerating the Problem Definition phase. As illustrated in Fig. 3 (below), modern problem solving approaches are highly dependent on the synthesis of knowledge across many disciplines. This is best accomplished through the integration of knowledge from many sources such as the biomedical literature (e.g. PubMed), descriptions and catalogs of biochemical pathways (e.g. Reactome), sources of information and knowledge about drugs (e.g. Drugbank), and maps of diseases and their relationships (e.g. Diseaseome). Knowledge engineering tools such

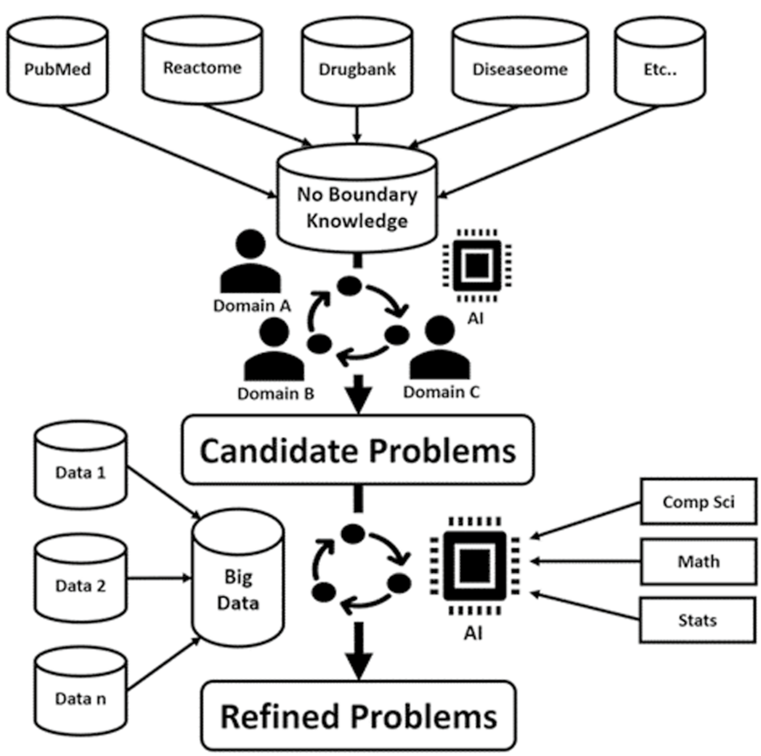

Fig. 3 AI as an accelerator agent for research in biomedical data analysis

as biomedical ontologies and graph databases facilitate structured integration of knowledge sources that allows for modeling entity relationships and complex queries. The key aspect of knowledge integrated in this manner is that it is agnostic to scientific or clinical discipline. An example resource that employs this kind of broad knowledge integration is the Alzheimer's Disease Knowledgebase or AlzKB that brings together knowledge from more than 20 different public knowledge sources [48].

Artificial intelligence can play a central role in Problem Definition by synthesizing integrated knowledge to assist diverse teams from different domains with identifying new problems. The advances in deep learning and LLMs make it possible to develop AI tools specifically for this purpose. The challenge is to tailor them specifically to the task of problem definition and refinement. For example, LLMs do not perform well when asked to query an integrated knowledge base such as AlzKB because they did not have access to the higher-level synthesis provided by the biomedical ontology and graph database used in the construction of the resource. Special computational methods such as retrieval augmented generation (RAG) and graph of thoughts (GoT) are needed to teach the LLM about the content of the knowledge base [49].

The end goal is to open new avenues of investigation that were not previously being studied. This is important because this is where fundamental new discoveries will come from. A historical example of what modern interdisciplinary approaches are trying to accomplish is the role of the apolipoprotein E (ApoE) gene as a major risk factor for Alzheimer's disease (AD). More than 30 years ago ApoE was studied as a risk factor for coronary artery disease given its role in cholesterol metabolism. After the ApoE protein was unexpectedly found in the brains of Alzheimer's patients it became a new problem that prompted genetic studies showing that certain combinations of alleles were significant risk factors [46]. The ApoE gene, its protein, and its interacting factors have been the focus of intense investigation for several decades [27]. We put this forward as an example of a new problem that was defined moving from the discipline of cardiology to neurology and psychiatry. It is our working hypothesis that new problems like this will be defined using integrated knowledge bases with synthesis provided by diverse teams augmented by AI.

For example, AI can be prompted to identify biochemical pathways that have treatments approved by the FDA, that have not yet been associated with AD. This can assist with defining new genes to investigate for feasible AD drug targets.

Discussion

The authors and countless others have spent significant effort defining and promoting interdisciplinary, trans-disciplinary, No-Boundary, and convergence research. research, but very little has been written about how we are to engage diverse teams of experts to carry out these modern approaches to research. Here we have highlighted how recent developments in data-enabled intelligent computing are assisting problem definers and solvers. Consistent with the desired modern principles of engaging multiple perspectives in research, we also have pointed to team formation and management practices from other disciplines that we believe can help diverse teams. In this section we will provide some suggestions gleaned from other bodies of knowledge and from our own observations while attempting interdisciplinary research. These are not meant to be prescriptive, but only suggestions that may assist in choosing the best processes for each team and problem.

While these practices may impose extra effort and time upon scholars trained in reductionist and single-disciplinary strategies for problem solving, research indicates that complex problems are likely to yield more easily to teams with diverse expertise [50]. It is not a matter of slowing or speeding up the pace of discovery, but instead a concern for the limited quality and feasibility of solutions derived under only one perspective (the effect of T-filtering, if you will). The project examples given above are meant to show efforts to carry out interdisciplinary, convergent and/or NBT research. Each used the technologies of their time to support their work. In some cases, game-changing AI was not yet used or available to enable more broad perspectives. Each exhibited several important team formation and operational characteristics that are worthy of mention.

With the addition of modern AI technology, it is expected that research will be further enhanced as new information arrives and scholars revisit their problem formulation and solution phases. The discussion points below are examples of practices that have helped to enhance the problem-definition phase.

Below we highlight elements of the evacuation and supply chain example projects that show evidence of desired diverse team principles. We also highlight how AI can strengthen our ability to accomplish the primary goals, especially the synthesis of volumes of information from multiple perspectives to define and solve difficult problems, and to efficiently adapt our approaches to factor in newly developing and incoming information.

- A fuzzy problem presents itself, and a small interdisciplinary group works to define the problem with teammates. The team size and the number of different perspectives grow as the project proceeds and additional expertise is needed to crisply formulate the problem. This was present in both the evacuation and supply chain examples. The use of AI as illustrated in the "Using AI to enhance problem definition" section shows how AI can efficiently provide access to information from more and diverse perspectives and enhance the important problem definition process.
- The whole team, including students, show each other the normal means of communication through artifacts and vocabulary in their own disciplines, then work together to develop an agreed upon and understood means to crisply define and express the problem and solution through a common vocabulary and set of artifacts [28]. This was strongly present in the evacuation project, with the presence of the cognitive modeling expert, and significantly accelerated the development of the problem and solution. The supply chain example was a PhD dissertation, so the PhD student researcher had to provide this kind of convergence in representation of the problem by synthesizing the various perspectives, vocabularies, and types of artifacts after meeting and discussing with mentors individually. The "Using AI to enhance problem definition" section shows how AI can be used as a powerful team member, but also shows that human intelligence is still needed, highlighting that human and machine intelligence each have different strengths, and when used together, can provide strong synergetic outcomes.

- A team meets regularly throughout the duration of the project with all partners to discuss all aspects of the problem and solution. This was a feature of the evacuation project. The supply chain project convened all perspectives through regular discussions with the lead researcher (the PhD student scholar) as a hub for discussion and decision-making. This was a PhD dissertation[3]; thus, this kind of hub and spokes structure of communication was assumed. While AI is not a human team member that can "meet" regularly, it can be regularly used in different phases of the project, such as identifying candidate problems, finding related work, computing results with identified models in data rich environments, etc.
- Industry experts and disaster response experts all meet with the team to explain their understanding of the problem and current shortfalls in response and guidance for pedestrian evacuation. They are invited early during problem definition and then later to review and validate the solution. Note the elements of Use-Inspired Research [51], including the problem arising from real-world needs, and the cycling between practitioners and scholars to better refine and solve the problem. The supply chain project, given that it was through a college of business, necessarily made significant use of industrial data and information. AI can efficiently assist in cycling between related data and research results with its ability to access and synthesize larger volumes of digital information that humans typically would struggle to process.
- An NBT team concludes and disseminates the research results as a team. The whole evacuation project team contributed to the validation and adjustment of the finalized simulation and dissemination of results. Each scholar led the writing of a paper tuned to venues in their own discipline but included the whole team as active co-authors. There was very little "parallel play" throughout all stages of the project. The doctoral research project necessarily required that all partners read and approved of the finalized dissertation. The PhD student scholar published papers of the research results with the assistance and editing of the members of the dissertation committee. The AI assistant can assure that a large and diverse body of references can be located and considered.
- The lead scholar assures that all voices are heard, including students, faculty scholars, and outside partners, and that respect for all perspectives was present. This was clearly present in both projects. The whole team assures that the AI team member is fact checked to assure that the information is accurate and makes scientific sense.

Suggestions for teams that may ease the difficulties that working in teams with diverse perspectives introduces:

- **Time** is needed to manage the communications among team members who are trained differently. Scheduling regular all-hands meetings to intentionally support such communications is helpful, especially at the beginning of a project. Short talks

[3] Note that because one project discussed above was a PhD dissertation, it was necessary for the student scholar to provide their own means of convergence at times. Perhaps this speaks to the need to reconsider the usual model for the conduct of student research, requiring more collaboration and regular meetings with multiple mentors, as opposed to the traditional model of independent research with significant involvement of only the major advisor. This would help to train scholars in the NBT mode, and not require additional training when they move on to conduct more integrated NBT research once the PhD is completed.

by disciplinary experts with time for questions and discussion to explain the perspectives of a given domain can also help to save time later during the problem-solving phase. While parallelizing activity in some sub-problem tasks can save time, "parallel play" without ample communications among sub-teams can lead to fragmented solutions that are difficult, maybe impossible, to integrate at the end of the project.

- **Communication** among team members trained in different modes. Each discipline has developed acronyms and technical terms (for efficiency of communication), and specific taste in types of problems to solve. When working in a team with members from different domains, it is important that each member communicates these concepts well to others. Each partner should have time to do this with others in the team. The team can then consider converging on a common set of terms and acronyms appropriate to the problem. Embracing a common means of conceptually representing and modeling project artifacts can also be effective [28]. It can help to promote deep integration of among problem solvers and their strategies as a team. It is fortunate that the biological and biomedical sciences share common constructs, data, mechanisms, such as DNA or RNA data and biological pathways, making it more straightforward for the discovery of similar problems and solutions, thus enabling the opening of the T-filter to multiple disciplines and perspectives.
- Fostering **respect** for all perspectives. Interdisciplinary teams are frequently made up of individuals from different career stages. Respect for those having more experience and position can sometimes silence important perspectives from other team members. Teams that show respect for contributions from all team members are likely to be more effective. While teams need to come to a consensus when solving a particular problem, it is important to not silence teammates who do not wield as much power or gravitas as others, especially during brainstorming sessions.
- **Flattening the hierarchy of power** in the team. While all teams will need a leader or manager, teams with flattened structure can support better collaboration among teammates. This will also support respect among teammates (see bullet above),
- Promoting collaboration but **preventing "group think"** [52] has written about how group think occurs and documented some of the tragic results that could occur with this happens. Thinking carefully about the balance between taking time to consider alternative perspectives and converging on an agreed upon means of moving forward is important. This includes the perspective of intelligent digital applications that analyze data and present results that should be carefully considered, but not automatically accepted. See [53] , for example, on how special attention to nature, source, organization of the data being automatically analyzed is important to assure ethical processing of information and that the AI is not simply enhancing human prejudices embodied in the data.
- **Patience** over the time dimension. The management of incoming information during the evolution of the project can be difficult. Patience in the process with acknowledgment that some team strategies and results will have to be adjusted as new information arrives is helpful. Patience is also needed when team members feel disoriented and experience paradigm shifts [12] when working closely with teammates from other disciplines and perspectives. Early discussions about this phenomenon as the team is forming and formulating the problem can help teammates to be patient

when disorientation occurs. Some of this was evident in the government and medical teams that had to inform and make policy decisions during the COVID pandemic. The results of the research had to be disseminated and implemented quickly. This also speaks to keeping the practitioner community well informed and patient while incoming information changes the translated guidance. Using automated and intelligent assistants can help to speed up these processes and stay informed of new information and developments.

- Using **technology to assist and manage the volume of information**. Our example above of the use of AI in the Alzheimer's Disease Knowledge Integration projects shows the power of computation in assisting the Problem Definition phase, especially when working with large or difficult data sets (Big Data). However, providing time to train teammates on the nature and use of such tools is helpful. While new technology typically enhances our problem-solving abilities, it always brings with it potential dangers that should be acknowledged and considered. Teammates who have learned to be patient and agile in the use of newly emerging tools are valuable.
- **Patience, empathy and listening**[4] are important skills for research teams. Absent these skills some teams could have trouble in attaining the deep integration needed to define and solve difficult problems. Teammates trained in presenting rhetorical arguments for their perspective on the problem are very valuable, as are those who are willing to mentor others in this valuable skill.

Interdisciplinary can be viewed as a process of processes, i.e. meta-process. The scientific research community is finally catching on to the fact that synthesis of all reductionistic results needs to be made. We need to see and understand how all the individual parts play a role and contribute to the larger system. This is what systems science has been promoting for many years [54]. It is also a natural outcome we have seen from disciplinary sciences (e.g. biologists embracing systems biology, and bioscientists and computational and mathematical scientists collaborating in bioinformatics). As the tools and technologies have enabled greater advances and wider perspectives, we now can leverage them in coming up with more comprehensive and effective solutions [55]. As data sources become more abundant and more sophisticated tools are developed, we can mine these to obtain more inferences.

The future of scientific research

In this paper we reviewed the definitions of various diverse teams approaches to and how they might benefit from approaches from other paradigms of research that call for teams of experts with diverse perspectives. We gave some examples of projects that have applied some of these methodologies in forming and managing their research teams. We also highlighted best practices from these projects and from other disciplines such as team science and systems engineering in the hopes that this information will help newly forming teams to come closer to the their research goals. We also focused on AI as a new

[4] Notes on effective interdisciplinary teams are taken from a talk by Caroline Guttschalk Druschke to a graduate class at the University of Rhode Island. Druschke is currently Professor of English, focused on rhetorical theory and freshwater science and management at the University of Wisconsin-Madison.

team member that might assist in increasing the flow of information from a wider range of sources through the T-filter. It is clear from our examples that the biomedical sciences benefit from the ability to find data from similar sources across different sub-disciplines in this era of abundant data, but *more needs to be done to properly abstract the underlying scientific constructs so that AI can more easily determine when information and problem types are similar and could be solved using similar techniques*.

New technologies and social insights on how diverse teams work best are likely to continue to emerge. For example, quantum computing is likely to speed up the processing of large volumes of data, and digital twin technologies will likely enable understanding of their "real-world" counterparts in real time and will use embedded AI to promote deeper understanding and enhanced prediction. We need to be open to emerging technologies and how they may assist in the Problem Defining phase, not just the Problem Solution phase.

In closing, we predict that we are entering a new era where we will be applying sophisticated technologies, such as artificial intelligence and whatever successors may be developed, in ways that enhance our ability to define more relevant problems-and this contribution may ultimately prove to be even more valuable than their application to the Research phase. As we gain the ability to synthesize more and more knowledge sources into our problem defining efforts, we will be able to effectively address the wicked and complex problems that we are encountering more frequently.

Furthermore, it is critically important that we begin to train the next generation of scientists in the interdisciplinary team processes so that they may be more productive in their careers.

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Authors' contributions
JHM and JP conceived the manuscript idea. TO and SFJ worked on initial manuscript draft as well as the literature review and background content. YZ worked on the Interdisciplinary Science section while JP worked on the Team Science and Systems Thinking sections. KLL, JP, and JHM provided content for the examples. JP worked on the discussion section. SFJ was responsible for the manuscript structure and alignment. TO oversaw the manuscript writing process. All authors (TO, SFJ, YZ, KLL, JP, and JHM) were involved with manuscript edits and revision.

Declarations

Competing interests
The authors declare that they have no competing interests.

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