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Article

Methods for measuring social and conceptual dimensions of convergence science

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Abstract

Convergence science is an intrepid form of interdisciplinarity defined by the US National Research Council as 'the coming together of insights and approaches from originally distinct fields' to strategically address grand challenges. Despite its increasing relevance to science policy and institutional design, there is still no practical framework for measuring convergence. We address this gap by developing a measure of disciplinary distance based upon disciplinary boundaries delineated by hierarchical ontologies. We apply this approach using two widely used ontologies—the Classification of Instructional Programs and the Medical Subject Headings—each comprised of thousands of entities that facilitate classifying two distinct research dimensions, respectively. The social dimension codifies the disciplinary pedigree of individual scholars, connoting core expertise associated with traditional modes of mono-disciplinary graduate education. The conceptual dimension codifies the knowledge, methods, and equipment fundamental to a given target problem, which together may exceed the researchers' core expertise. Considered in tandem, this decomposition facilitates measuring social-conceptual alignment and optimizing team assembly around domain-spanning problems—a key aspect that eludes other approaches. We demonstrate the utility of this framework in a case study of the human brain science (HBS) ecosystem, a relevant convergence nexus that highlights several practical considerations for designing, evaluating, institutionalizing, and accelerating convergence. Econometric analysis of 655,386 publications derived from 9,121 distinct HBS scholars reveals a 11.4% article-level citation premium attributable to research featuring full topical convergence, and an additional 2.7% citation premium if the social (disciplinary) configuration of scholars is maximally aligned with the conceptual (topical) configuration of the research.

Keywords: convergence; team science; team assembly; ontology; interdisciplinary distance; alignment.

The scientific frontier is increasingly characterized by domain-spanning problems calling for the strategic integration of disparate domains of expertise to strategically address high-stakes challenges faced by society (Helbing 2012, 2013; Petersen, Ahmed and Pavlidis 2021). In response, the convergence science paradigm—defined by its originators as 'the coming together of insights and approaches from originally distinct fields' (National Research Council 2014)—has emerged as an organizational model constructed around a mission-oriented agenda that promotes social-engineering to fortify existing interdisciplinary approaches to addressing boundary-spanning grand challenges (NSF, accessed February 2021). With team science becoming the predominant mode of knowledge production (Wuchty, Jones and Uzzi 2007; Börner et al. 2010; Pavlidis, Petersen and Semendeferi 2014; Petersen, Pavlidis and Semendeferi 2014), convergence represents a holistic strategy for harnessing social and conceptual diversity, and for accelerating action on multi-dimensional problems (Page 2008; Linkov, Wood and Bates 2014; Pavlidis, Akleman and Petersen 2022). Specific examples include deforestation and illicit wildlife trade (Di Minin et al. 2018; Arroyave et al. 2020, 2021), two wicked problems that span sociocultural, technological, political, and environmental dimensions (Orsatti, Quatraro and Pezzoni 2020).

Even in the best-case scenario, where traditional mono-domain approaches exist that address certain facets of the target problem, convergence is needed to address the multi-dimensionality of such problems, as partial solutions are likely to be fragmented and all together incomplete (Linkov, Wood and Bates 2014). As such, designing and assembling a complete and feasible composite solution is a principal barrier to addressing grand challenges. Another reason multi-dimensional problems call for convergence is due to the intrepid interdisciplinary distances commonly entailed, which can alter the required assumptions and generalizability of mono-domain approaches. All together, the integration of disparate disciplines and their specialized capabilities is unlikely to be straightforward or clear. However, by extending principles of recombinant innovation (Weitzman 1998; Fleming 2001; Orsatti, Quatraro and Pezzoni 2020) to social-engineering contexts, effective multidisciplinary integration can be achieved by repurposing and reconfiguring of disparate elements—such as scholars of varying expertise, and conceptual theories and methods—into a configuration that represents a specific strategy (a key) that sufficiently satisfies the constraints associated with all facets of the domain-spanning problem (the lock). For this reason, exploiting diversity also serves a valuable hedge against the uncertainty inherent in exploring the space of relevant and accessible social and conceptual recombinations (Fleming 2004; Orsatti, Quatraro and Pezzoni 2020; Petersen 2022).

Owing to these considerations, the application of convergence science to domain-spanning problems can clearly be recast as a social engineering or team-design problem—one that calls upon principles of recombinant innovation and function-oriented design in order to best address the boundary conditions imposed by the governing agenda and the challenge itself. Consequently, convergence science differs from other established modes of interdisciplinary research (IDR) in two ways. First, convergence entails a governance model that establishes a specific agenda delineating a clear set of incentives, constraints, definitions, and objectives upon the principal actors—as is typical of flagship funding programs funded by national innovation systems, an example being the Human Genome Project (Petersen et al. 2018). This consideration distinguishes convergence from IDR, the latter tending to be more broadly defined and interpreted, including teams and concepts formed under spurious conditions, and thereby featuring piecemeal distinctions between disciplinary components. The second distinction requires comparison with transdisciplinary research (TDR), defined as research 'transcending and integrating' (Carew and Wickson 2010) multidisciplinary methods and objectives (Colón et al. 2008) in order to harness cross-sectoral and cross-disciplinary diversity that is broad in scope (Klein 2006; Belcher et al. 2016; Laursen, Motzer and Anderson 2022)—but with no conditions on the characteristics of the target problem. According to this juxtaposition, convergence is thus key to *multi-dimensional problems* requiring *strategic* integration of *disparate* domains of knowledge, academic disciplines, public and private sectors that span *intrepid* distances (see Figure 1). This distinction thereby calls for both clear problem-solving agenda setting, often imposed or incentivized via a funding body, as well as social engineering to integrate disparate domains according to principles of structural and functional relatedness (Hidalgo et al. 2018), thereby requiring an operational distance metric.

Despite a rich literature on approaches to evaluating IDR (Wagner et al. 2011; Laursen, Motzer and Anderson 2022), extant methods are insufficient for measuring and evaluating convergence science. Instead, a candidate evaluation method should be able to (i) account for the distances between components of the target problem and (ii) evaluate how aligned is a given team with the problem it was designed to address. It follows that such a framework for measuring and evaluating convergence strategies and their research outcomes must implicitly distinguish between social and conceptual dimensions. Such a distinction not only owes to the significant organizational and financial costs of transdisciplinary team assembly, as it is common that the conceptual dimensions of a problem exceed the researchers' core expertise. The distinction is also fundamental to evaluating social-conceptual alignment, which is critical to accounting for the significant risk and uncertainty associated with high-stakes domain-spanning problems.

To address these issues, we leverage two distinct hierarchical corpora of social and conceptual entities, each endowed with relational structure that facilitates inferring disciplinary boundaries and distances between entities. In the case of the conceptual dimension of research, we utilize the Medical Subject Headings (MeSH) ontology comprised of ~30,000 keywords located across 13 hierarchy levels, which provides ample room for adaptation and specification to address the broad applications of convergence science. Similarly, we codify the social configuration of a research team according individual authors' departmental affiliations, which connote specific socially endowed domains of expertise. This definition of disciplinary expertise reflects the traditional modes of mono-disciplinary education imprinted upon the bureaucratic organization of the modern research university. Hence, to identify disciplinary boundaries and distances, we employ a hierarchical ontology designed for classifying all higher-education degree-granting programs in the USA. Considered in tandem, the deconstruction of research outcomes according to these two dimensions facilitates measuring social-conceptual alignment and optimizing team assembly around domain-spanning problems—a key aspect that eludes other approaches.

Against this backdrop, we contribute to the growing literature on convergence science by developing a highly generalizable and extendible measurement framework, and demonstrate its utility in a comprehensive data-driven analysis of the global convergence frontier emerging in the human brain sciences (HBS) (Petersen, Ahmed and Pavlidis 2021). This framework contributes to research on interdisciplinary evaluation (Wagner et al. 2011; Laursen, Motzer and Anderson 2022) and science of science policy (Fealing 2011) that are critical to supporting design-oriented approaches to TDR (Colón et al. 2008; Carew and Wickson 2010). To this end, we seek to address the following research questions (RQs):

RQ1: How is convergence distinguished from interdisciplinary research, and how does the mission-oriented distinction inform the design of a measurement framework for deconstructing convergence along its principal social and conceptual dimensions?

RQ2: How to operationalize a disciplinary distance metric for measuring neighboring versus distant ('originally distinct') domains, a concept that is fundamental to the original definition of convergence?

RQ3: How can existing and widely used hierarchical ontologies be used to define and codify the disciplinary boundaries that are essential to measuring convergence as strategic configurations spanning 'originally distinct' domains?

RQ4: How can analyzing the social and conceptual dimensions of convergence in tandem inform our understanding of both the inherent challenges and deep potential underlying this more agenda-oriented and agenda-constrained transdisciplinary paradigm?

RQ5: And given the importance of strategically assembling teams that optimally address complex multi-dimensional problems, to what degree is social-conceptual alignment achieved in human brain convergence science? And to what degree does convergence in either of the social or conceptual dimensions, along with their alignment, effect research outcomes?

In what follows, we first provide a review of this important paradigm and ongoing convergence nexuses championed by the US National Science Foundation (NSF) 'Convergence Accelerator'. We then develop a framework for measuring the recombinant dimensions of convergence. We then apply this framework to a comprehensive dataset capturing the HBS nexus (Petersen, Ahmed and Pavlidis 2021), which is an exemplary mission-oriented domain with various multi-billion dollar international flagship funding initiatives calling on convergence at the intersection of neuroscience, population health, public policy, law, big data, genomics, cognitive

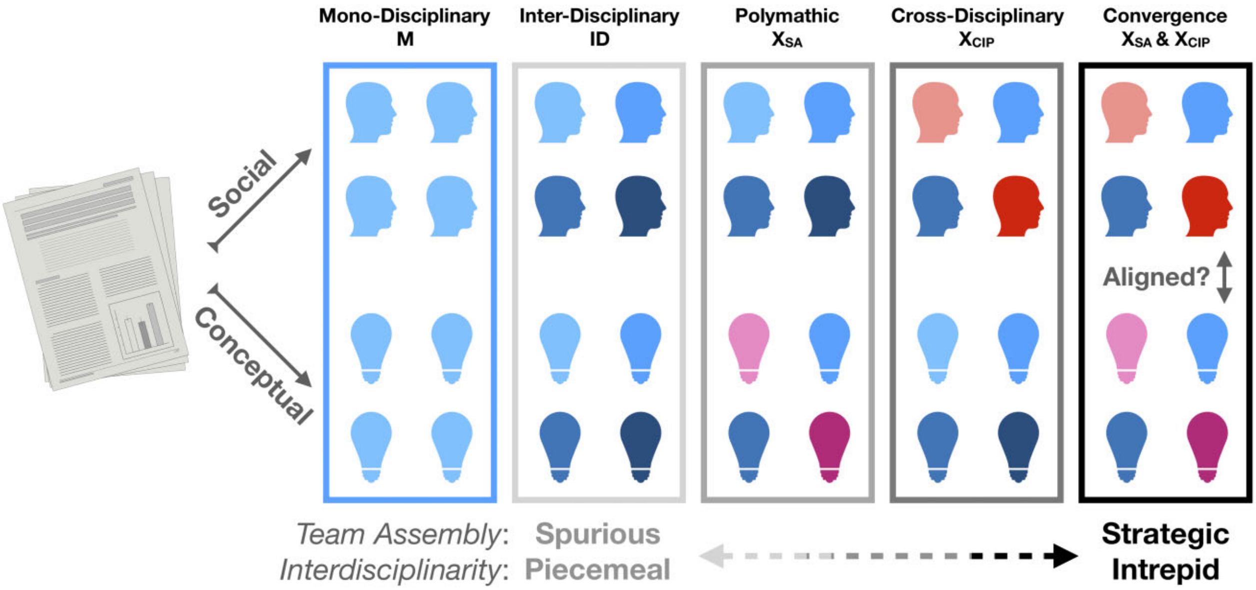

Figure 1. A definition of convergence by way of its deconstruction along social and conceptual dimensions. Convergence is achieved by way of strategic team assembly that leverages synergies among originally distinct domains to address specific target problems defined by a mission-oriented agenda. According to this definition, convergence is an intrepid form of interdisciplinarity, distinguished from more happenstance manifestations of piecemeal integration, and instead requiring a consistent and robust measurement framework that facilitates evaluating (mis)alignment across both social and conceptual dimensions (Wagner et al. 2011), which is an essential task of research project selection, evaluation, and assessment. Accordingly, in this schematic, the different shades of a common color base indicate neighboring domains characterizing piecemeal diversity, whereas different color bases (e.g. red, blue, magenta) indicate more intrepid configurations spanning distinct social and conceptual domains. Two partial modes of convergence can thus be codified and identified (Petersen et al. 2018; Petersen, Ahmed and Pavlidis 2021; Pavlidis, Akleman and Petersen 2022; Yang, Pavlidis and Petersen 2023): (1) *polymathic* research (represented as X_{SA}) integrates distant concepts and methods by way of expansive learning by a team featuring more narrow disciplinary diversity and (2) conversely, *cross-disciplinary* research (X_{CIP}) features multi-disciplinary teams focusing on problems spanning a relatively narrow conceptual scope. According to this framework, complete convergence ($X_{SA\&CIP}$) incorporates both modes of cross-domain integration, with the additional requirement of evaluating the quality of alignment between the social and conceptual configurations. Conceptualized as such, distinguishing $X_{SA\&CIP}$ from IDR requires operationalizing a distance between social and conceptual entities defining a given research agendas and its output, which is the main methodological contribution of this work.

science, and a myriad of other sciences (Dzau and Balatbat 2018). And we conclude with outlook and policy recommendations addressing several practical considerations associated with designing, evaluating, institutionalizing and accelerating convergence.

Background and motivation

Convergence science—a mission-oriented paradigm for addressing transdisciplinary grand challenges

While the structure of convergence is multi-dimensional (social and conceptual), the institutional scope of convergence is multi-level. At the highest level of aggregation are national innovation systems characterized as configurations of industry, university, and government that leverage cross-sectoral (e.g. triple-helix) synergies, whereby a common agenda that respects individual prerogatives and practices can be established around a common objective to promote economic growth (Leydesdorff and Etzkowitz 1996; Etzkowitz and Leydesdorff 2000; Stephan 2012). Such strategic synergies are also important to endeavors less appreciated as innovation and growth oriented, yet still relying on cross-sectoral knowledge co-production, such as protected area land management for preserving critical ecosystems (Arroyave et al. 2022). This model of integration-mediated innovation is readily extended to other domains of knowledge production that organize around the principle triple-helix components—namely, demand for solutions (applications), supply of knowledge (theory), and techno-socio-political capabilities (catalysts). For example, the biomedical health sector can be cast as a triple-helix forming around a disease, drug, and techno-informatic capabilities (Petersen, Rotolo and Leydesdorff 2016; Yang, Pavlidis and Petersen 2023), yielding breakthrough successes in the last two decades ranging from the map of the human genome (Petersen et al. 2018) to rapid development of COVID-19 mRNA vaccines; more prospective examples include the coming era of bio-mechatronics and human–machine systems (Kose and Sakata 2019; Pavlidis, Akleman and Petersen 2022). Principles and practices of convergence science can be applied to ongoing efforts to integrate non-STEM fields, such as humanities and arts, as demonstrated by STEAM and digital humanities initiatives that exemplify the integration of ‘soft’ and ‘hard’ methodologies (Pedersen 2016).

It is also notable that disciplinary convergence has a long-standing role as the counter-balance to divergence (Roco et al. 2013; Balietti, Mäs and Helbing 2015; Watson 2017; Pavlidis, Akleman and Petersen 2022). Yet the transition toward convergent problem solving has become integral to national innovation systems charged with developing mission-oriented agendas and policy (Fealing 2011; Wanzenböck et al. 2020). Convergence has been championed in the last decade by the US NSF, specifically the Office of Integrative Activities (OIA), which aims to accelerate problem-solving around specific target areas characterized by grand societal challenges (Helbing 2012) by calling for strategic collaboration across disciplines and sectors (National

Research Council 2014; NSF, accessed February 2021). By way of example, since launching in 2019, the 'Convergence Accelerator' program (NSF, accessed February 2021) has identified and funded research aligned with the following 13 challenge areas:

2019: Open Knowledge Networks (Track A); AI & the Future of Work (Track B).
2020: Quantum Technology (Track C); AI-Driven Innovation via Data and Model Sharing (Track D).
2021: Networked Blue Economy (Track E); Trust & Authenticity in Communications Systems (Track F).
2022: Securely Operating Through 5G Infrastructure (Track G; Jointly funded with the Department of Defense); Enhancing Opportunities for Persons with Disabilities (Track H); Sustainable Materials for Global Challenges (Track I); Food & Nutrition Security (Track J).
2023: Equitable Water Solutions (Track K); Real-World Chemical Sensing Applications (Track L); Bio-Inspired Design Innovations (Track M).

As evident in titles alone, these nexuses are integrative by design and are likely to spur novel configurational synergies to support the emergence of new hybrid disciplines such as genomics (Sharp and Langer 2011; Petersen et al. 2018) and to address the 'hard problems' associated with complex systems that are exacerbated by human behavior (Bonaccorsi 2008; Oreskes 2021).

Summarizing according to the schematic in Figure 1, convergence is an extended mode of TDR (Colón et al. 2008; Carew and Wickson 2010) distinguished from more common and piecemeal forms of interdisciplinary activity (Pan et al. 2012; Leahey and Moody 2014) in two ways. Specifically, convergence calls for synergistic alignment between (1) originally distinct domains that integrate according to (2) strategic configurations that satisfy the constraints of the mission-oriented agenda and the grand challenge itself—with the latter being a more strict condition distinguishing convergence from transdisciplinarity. Yet there are no well-defined methods for measuring convergence according to these operational differences—which is the main methodological contribution of this work.

Extant methods for science mapping

Our framework for operationalizing a disciplinary distance metric builds upon prior methods for defining and visualizing topics, field, and disciplines. Such cartographic approaches to science mapping vary according to their inputs, assumptions, and granularity, but the overall objective is to convey a representation of ontological difference based upon the spatial proximity of entities projected onto a two-dimensional surface. Disciplinary mapping methods rely on information embedded in citation networks (Rafols, Porter and Leydesdorff 2010; Carley et al. 2017), pre-defined categories (Leydesdorff, Carley and Rafols 2013; Yang, Pavlidis and Petersen 2023), cognitive proximity (Grauwin and Jensen 2011; Arroyave et al. 2021), and semantic similarity of natural language (Suominen and Toivanen 2016; Velden et al. 2017), among others. Despite these differences in their methodological and empirical foundations, comparative analysis indicates that resulting cartographies of science do not differ significantly (Velden et al. 2017).

One popular approach is science overlay mapping (Rafols, Porter and Leydesdorff 2010), which has recently been improved to incorporate hierarchical structures (Sjögårde 2022). While such refinement could be used to define disciplinary categories, and to some extent hybrid categories representing multidisciplinary mixtures, this approach still requires an additional manual annotation step, i.e. assigning labels to the resulting categories, which is subject to annotator bias. Another limitation to science mapping is its focus on research outcomes (publications) rather than the researchers themselves (authors), and is thus insufficient for typologizing the disciplinary composition of teams. Furthermore, science maps inherit the biases present in the data inputs, examples including the under-representation of social sciences, arts, and humanities books along with engineering conference proceedings in many publication repositories. Extending this argument further, it is also likely that classification of cross-sectorial research (e.g. involving industry and policy actors) will under-represent the transdisciplinary composition of research teams and research outcomes.

Another nuanced point regarding science maps inferred from citation networks is the representations are confounded by endogenous trends in cross-disciplinary mobility and scholarly citation practices (Petersen et al. 2018). More specifically, it could be expected that disciplines that were originally distinct decades ago (e.g. computer science and biology), have drawn more close given the emergence of hybrid sciences at their boundaries (e.g. genomics, computational biology). In other words, the paradigm of IDR tends to naturally increase the relatedness of originally distinct field. Consequently, we argue that both exogenously defined ontologies and epistemological approximations based on authors (disciplinary background and expertise) are needed in order to identify the convergence of teams working on boundary-spanning problems.

Extant methods for measuring IDR and limitations to measuring convergence

There is no well-established approach to defining distances between disciplines, neither in philosophical foundations nor in the IDR evaluation literature (Nissani 1995; Barry, Born and Weszkalnys 2008; Wagner et al. 2011; Laursen, Motzer and Anderson 2022). This methodological gap is conveyed in Figure 1 by the ID column: while traditional IDR methods have been developed for measuring the variety of social or conceptual types featured by research, they are insufficient for identifying whether those types are piecemeal variants of the same concept, or conversely, represent substantial cross-domain combinations of originally distinct concepts and methods. By way of example, two neighboring variants within the same conceptual domain are 'Computer Science' (CIP 11.07) and 'Information Science' (CIP 11.04). Instead, two variants that may at first appear to be similar but derive from distinct origins are 'Phenomics' (MeSH E05.588.570.700, described as 'The systematic study of how genetic information or genomics translates into biochemical, metabolic, and morphological traits of an organism') and 'Protein Array Analysis' (MeSH E05.588.570.700, 'Ligand-binding assays that measure protein–protein, protein–small molecule, or protein–nucleic acid interactions using a very large set of capturing molecules, i.e., those attached separately on a solid support, to measure the presence or interaction of target molecules in the sample') represent altogether different approaches to operationalizing biological research—the former representing *in silico* and the latter being *in vitro* approaches. One also encounters various approaches in the IDR literature for measuring disciplinary diversity as either variety, balance and/or disparity, or as a combination (Harrison and Klein 2007; Stirling 2007; Rafols and Meyer 2010).

Another issue is that the underlying data used to quantify variety, balance and disparity are typically derived from 'flat' (i.e., non-hierarchical) classification systems that were originally designed for altogether distinct library science objectives, namely cataloguing journals. The main advantage of flat classification systems is they are simple. And because there is no structure associated with the categories, the category systems can be readily extended without having to also amend the relationships between categories.[1] As such, these flat classification systems are conveniently available in large publication indices such as Clarivate Web of Science (WOS) and Scopus (namely, the WC and SU fields in the former index, and the 'Subject Areas' field in the latter). And while the research area (SU) classification does feature entities grouped according to five broad categories (Arts and Humanities; Life Sciences and Biomedicine; Physical Sciences; Social Sciences; Technology), these categories lack the granularity needed to establish distances in-between the two extremes of heterotype and homotype. Because most classification systems lack the requisite resolution for delineating more nuanced disciplinary boundaries, they are not appropriate for measuring convergence. One manifestation of this inadequacy is the 'multidisciplinary' category applied when a type does not fit neatly into an existing category, which is increasingly common, and speaks to the relevance of identifying a more robust and objective approach to identifying boundary-spanning configurations. In order to measure the similarity or distance between categories, metrics such as the Stirling Index and other variants call for ad hoc assignment of a distance d_{ij} between any two categories i and j (Stirling 2007; Leydesdorff, Wagner and Bornmann 2018, 2019). Nevertheless, without subjective manual grouping of journal categories into disciplinary clusters, there is no objective rubric for identifying whether a given journal category combination represents convergence.

This may be the most critical disadvantage of commonly used classification systems—i.e., their intended design for classifying journals, and not individual research articles (Boyack and Klavans 2011). In addition to lacking information regarding the distance between different categories, flat classifications tend to over-generalize disciplinary content. This issue was demonstrated in a study by Leydesdorff and Opthof (2013) showing that research published on a very narrow conceptual topic 'Brugada Syndrome' nevertheless maps onto 24 different WC. This example shows how WC lack information specifying relationships between categories that could be used to counter the tendency for category diversification, which is an advantage of relational ontologies. Moreover, the vast majority of journals, and hence all articles published by that journal, are classified by a single category (see Supplementary Appendix for specifics on WOS), and the assignment of which has been criticized as being subjective (Boyack, Klavans and Börner 2005; Rafols and Leydesdorff 2009; Rafols and Meyer 2010; Leydesdorff, Wagner and Bornmann 2018). Consequently, these systems lack sufficient resolution to distinguish piecemeal interdisciplinary combinations from more intrepid cross-domain combinations.[2]

Indeed, if the technical objective is to classify and compare the content of individual research articles, then article-level keywords are more appropriate. Extant methods to define a keyword concept space include externally defined dictionaries (Leahey and Moody 2014) and clustering title and abstract words using natural language processing (Mane and Börner 2004). Ideally, article-level keywords are assigned based upon the article content only and are not conditioned by other information such as the journal; see Shu et al. (2019) on the differences between journal and article-level classifications. Another necessity is that keyword dictionaries be standardized—such as the 'Keywords Plus' (ID) recorded in WOS annotations, as opposed to alternative author-defined keywords (DE)—so that they are not subject to assignment idiosyncrasies associated with author, discipline, language, and international context. And as above with journal categories, if the organizational structure of the standardized keywords is flat then they also offer limited ability to measure cross-domain integration. Bibliographic coupling and keyword clustering approaches may provide a step in the right direction to develop measures of (dis)similarity by identifying topical or social groups based upon co-occurrence statistics (Velden et al. 2017).

A final limitation regarding the scope of approaches used in extant IDR literature is the relatively narrow focus on conceptual components (commonly identified by way of keywords or journal classifications) (Wagner et al. 2011)—as opposed to its social components. In what follows, we develop a parallel classification of social dimensions as informed by authors' departmental affiliations, which connotes scholars' particular domains of core training and expertise. Alternative approaches might involve classifying individuals according to their PhD field. Yet, because hiring culture in traditional academic settings has reinforced longstanding disciplinary identities connoted by departments, an author's departmental affiliation is likely to highly correlate with their PhD field, and so these two approaches are likely to yield the same insights. Such intra-disciplinary hiring bias is consistent with the strong role of prestige-oriented in-group sorting in faculty hiring (Wapman et al. 2022). Independent of the methodology for classifying social components, there are relatively few studies that systematically construct disciplinary categories based upon author attributes (see for example Qiu 1992; Qin, Lancaster and Allen 1997; Schummer 2004; Abramo, D'Angelo and Di Costa 2017; Petersen et al. 2021, 2018). One reason for this is the difficulty in obtaining and classifying unstandardized author affiliation metadata. As a result, many studies that take this approach are limited in data sample size (Schummer 2004; Wagner et al. 2011).

Advantages of hierarchical ontologies for defining distinct disciplinary domains

We address the aforementioned issues associated with defining distinct disciplinary domains by leveraging two existing hierarchical ontologies used to classify the social and conceptual dimensions of research, respectively: (1) the Classification of Instructional Programs (CIP) ontology comprised of 2,100+ educational program types, useful for classifying authors' departmental affiliations; and (2) the Medical Subject Heading (MeSH) ontology comprised of 30,000+

individual keywords spanning a wide range of biological and medical concepts. Both ontologies offer varying depth resolution due to their hierarchical design, and are sufficiently broad to support the evaluation of nearly all the 10 challenge areas listed above. For example, the CIP ontology includes a branch dedicated to 'Multi/Interdisciplinary Studies', including but limited to 'Science, Technology and Society', and 'Data Science'. Similarly, in addition to core biomedical and health concepts, MeSH also includes equipment, technology, methods, and other far-reaching entities representing intersections with other domains, such as 'sustainable development' and 'algorithms'. See the Supplementary Appendix regarding the scope and limitations of these ontologies.

Another advantage of thesaurus and entity-oriented ontologies, examples including MeSH and PhySH, is they can readily be combined by way of advanced alignment techniques (Wang et al. 2018), since they are comprised of objective entities as opposed to subjectively defined and broad categories. Notably, the PhySH ontology has replaced the longstanding PACS system used for decades to classify physics research (Smith 2019). Hence, the foresight of ontological design supports the generalizability and extendibility of our framework beyond the ontologies developed in what follows. As such, building on recent efforts (Petersen et al. 2021; Yang, Pavlidis and Petersen 2023), we use this convergence framework to develop useful methods for representing, visualizing, and quantifying convergence as cross-domain integration—corresponding to multidisciplinary integration if the domains being considered are disciplines; or epistemological integration if the domains correspond to research concepts.

Methods

Hierarchical CIP and MeSH ontologies for representing social and conceptual dimensions of research

The measurement of convergence requires a measure of a distance between any two given entities. As such, the first methodological imperative is to be able to identify whether two given entities are neighboring variants or sufficiently distant to qualify as belonging to 'originally distinct' domains (National Research Council 2014).

Figure 2A is a schematic that illustrates our method that leverages existing hierarchical ontologies to differentiate whether two concepts (alternatively departments) belong to the same or to distinct subject areas (respectively, disciplines). Neighboring and distinct domains are clearly delineated by the hierarchical structure of the ontology, and depend on the selection of an aggregation level parameterized by a level cut. The schematic shows a L_2 level cut, which thereby defines members of subgroups and establishes a first approximation of a metric distance according to the ontological lineage. Level cuts at higher levels of the hierarchy yield more distinct domains. The choice of the level cut facilitates variable domain resolution scales, e.g. see Yang, Pavlidis and Petersen (2023) for comprehensive historical MeSH co-occurrence analysis at both L_1 and L_2 levels.

The hierarchical structure facilitates aggregating counts for entities located above the level cut into the counts for their parent entity: for example, the hypothetical keyword 1.1.2.3 and 1.1.2 would both be counted as entity 1.1 for a level cut at L_2. Similarly, 1.1.2.3 and 1.1.3.3 would also be aggregated for a L_2 cut, but would be counted separately for a L_3 cut. This ability to merge entity counts facilitates establishing a weighted content representation, which is another advantage of our method.[3]

Based upon their locations in the ontology, the distance between any two entities can be objectively defined as neighboring (mono-domain) or distant (cross-domain). By way of example, our schematic illustrates how classifying all types within the hypothetical ontology according to the L_2 level produces six distinct sub-domains: category types 1.1 and 1.1.2 and 1.1.2.3 would all be classified as type 1.1, and all these types would be considered different than entities belonging to 1.3 (e.g. 1.3.1, 1.3.2, and so on). In this way, a hierarchical ontology yields a flexible basis set that offers a weighted vector representation of the conceptual (or alternatively, social) dimensions of a research article, as illustrated in Figure 2B.

Figure 3 illustrates two existing ontologies, one social and one conceptual, applied in recent research (Petersen et al. 2021, 2018, 2016; Yang, Pavlidis and Petersen 2023). In the case of the social dimension, we use the CIP ontology maintained by the US National Center for Education Statistics (National Center for Education Statistics 2022), which was developed for classifying instructional degree-granting programs for programmatic certification and assessment. Because faculty departments are typically strongly aligned with the degree-granting educational programs they offer, the CIP ontology is useful for measuring distances between disciplines as proxied by scholars' departmental affiliations, which can be inferred by information listed in an article byline or on their faculty home page or departmental home page. And with thousands of categories, the CIP ontology is sufficiently comprehensive to span the entire space of author affiliations. Also, a researcher could in principle have multiple primary affiliations, which could map onto two or more CIP categories. Such instances are likely to be exceptional corner cases where the individual represents a cross-disciplinary or hybrid scholar. However, if we restrict our annotation to primary affiliations (e.g. excluding courtesy appointments and external institutional affiliations), then such cases are likely to also be exceptional. Regardless, for each research article p (or any other research output, such as a patent or grant proposal) one obtains a count vector $\vec{v}_{CIP,p}$ by aggregating the CIP counts across the set of coauthors.

In the case of the conceptual dimension, we use the *Medical Subject Heading (MeSH)* ontology maintained by the US National Library of Medicine (US National Library of Medicine 2022), which is presently comprised of more than 30,000 MeSH terms organized in a 13-level hierarchical knowledge network that spans a number of distinct conceptual domains that are concentrated upon, but not limited to, biological, health, and medical subject areas (Yang, Pavlidis and Petersen 2023). Individual MeSH are assigned to articles indexed within the PubMed index by professional annotators using algorithmic assistance, which connote the principal entities entailed by the research, such as diseases, chemicals, syndromes, methods, equipment, etc. From 2022 onwards, annotation has become increasingly automated by way of the Medical Text Indexer algorithm (MTIA). MeSH is constructed according to a thesaurus, such that different terms map onto a single MeSH according to the variant 'Entry Terms' specified in each MeSH's description page. Hence, the MeSH ontology corrects for multiple and ambiguous

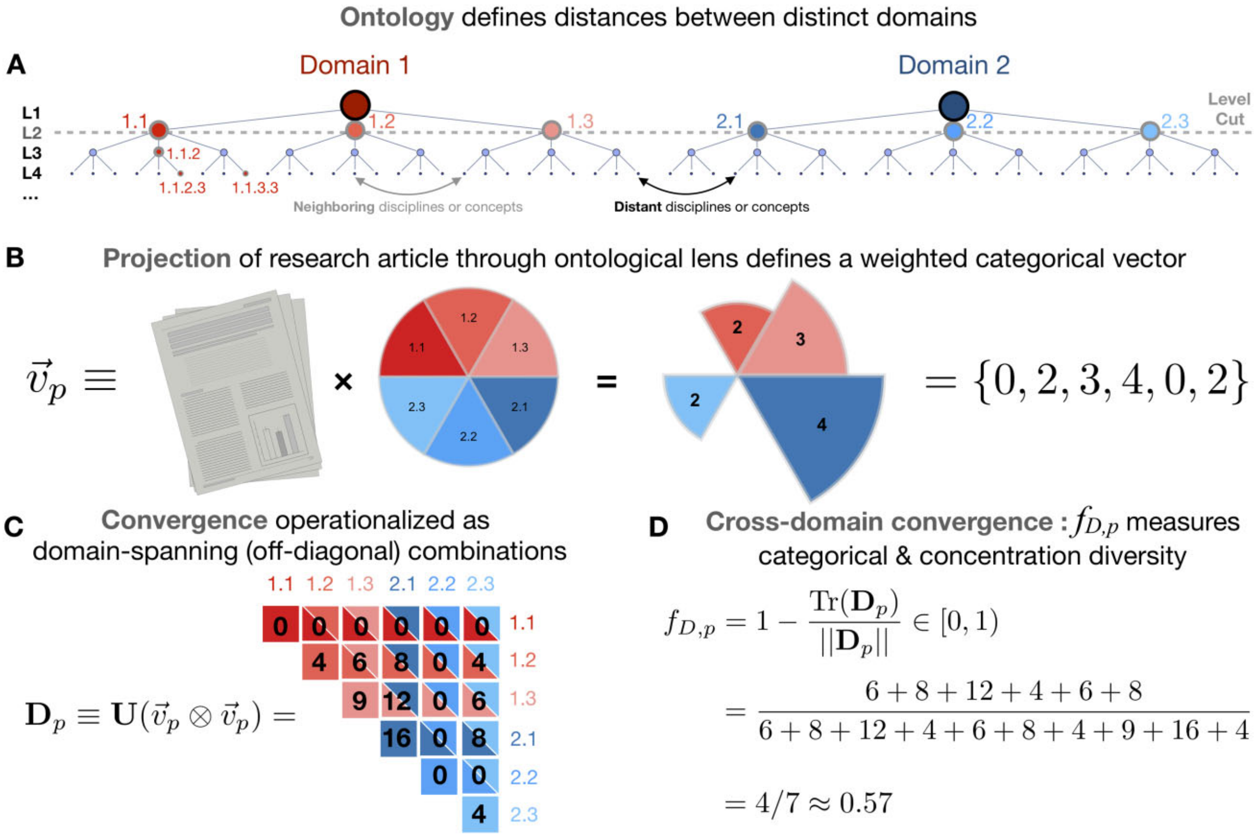

Figure 2. Measuring convergence as cross-domain integration. (A) Identifying boundaries that define distinct domains is an important step toward developing a metric distance between entity types, e.g. concepts or disciplines in the present case. To this end, the boundaries explicitly delineated by hierarchical ontologies are useful for classifying entities as neighboring variants, or alternatively, sufficiently distant so as to be considered 'originally distinct'—a dichotomy required for evaluating convergence (National Research Council 2014). (B) Projecting research outputs (e.g. a publication or patent or grant proposal, generically denoted by the index p), against a consistent framework yields the type-count vector $\vec{v}_p$. (C) As a combinatorial construct, we systematically measure convergence by way of the outer-product matrix that tabulates the proportion of each cross-domain combination (corresponding to off-diagonal matrix elements), relative to mono-domain concentrations (diagonal elements). (D) Illustration of simple steps to quantify convergence according to $f_{D,p}$ defined in Equation (1), which accounts for both categorical variation and concentration disparity (Harrison and Klein 2007).

meanings of individual descriptors. As in the case of multiple affiliations above, when a single MeSH maps onto multiple L_1 MeSH branches (a relatively infrequent case, corresponding to 6% of all MeSH (Yang, Pavlidis and Petersen 2023)), the ontology provides a systematic way for identifying and managing these edge cases. As such, each individual MeSH keyword is classified according to a given topical domain, which we call a subject area (SA). We then combine all the MeSH counts into a count vector $\vec{v}_{SA,p}$ for each article.

These examples highlight one of the advantages of hierarchical ontologies, namely they support identifying particular cross-domain configurations to be evaluated, which can be specified by the manual merging of distinct domains into a 'super-group'. By way of example, the color scheme in Figure 3 illustrates a manual merging of L_1 categories into three 'super-group' or L_0 domains: Health (purple); Science Technology Engineering and Mathematics (STEM; green); and Social Sciences, Humanities and Arts (SSHA; orange).

Measuring convergence according to boundary-spanning configurations

Because convergence is a fundamentally combinatorial construct, we operationalize it by tabulating all pairwise cross-domain combinations occurring in a given p. Figure 2C illustrates how all pairwise combinations can be represented by the tensor-product matrix $\boldsymbol{D}_p = \boldsymbol{U}(v_p \otimes v_p)$, where $\boldsymbol{U}$ represents an operator that selects the upper-triangular matrix elements, since convergence is operationalized as categorical combinations as opposed to permutations. Each matrix element $D_{ij} = v_i \times v_j$ corresponds to a simple Hadamard product of the corresponding vector elements (for $j \geq i$; conversely, $D_{ij} = 0$ for $j < i$, according to the arbitrary choice of $\boldsymbol{U}$ to correspond to upper- as opposed to lower-triangular elements). Rather intuitively, elements along the diagonal of $\boldsymbol{D}_p$ capture the relative weight of intra-domain combinations, whereas the off-diagonal elements capture cross-domain combinations. Additional higher-level organization, e.g. L_1 information encoded in the schematic as red and blue color schemes, can be inferred according to the location of each domain within the ontology.

Figure 2D illustrates a straightforward and intuitive measure of convergence, calculated as the relative contribution to $\boldsymbol{D}_p$ by off-diagonal elements, given by the fraction

$$f_{D,p} = 1 - \mathrm{Tr}\,(\boldsymbol{D}_p)/||\,\boldsymbol{D}_p\,|| \qquad (1)$$

where Tr $(\boldsymbol{D}_p)$ indicates the matrix trace corresponding to the sum of the diagonal elements, and $||\ldots||$ indicates the matrix total calculated by summing across all matrix elements. This measure is standardized in that its upper and lower limits are

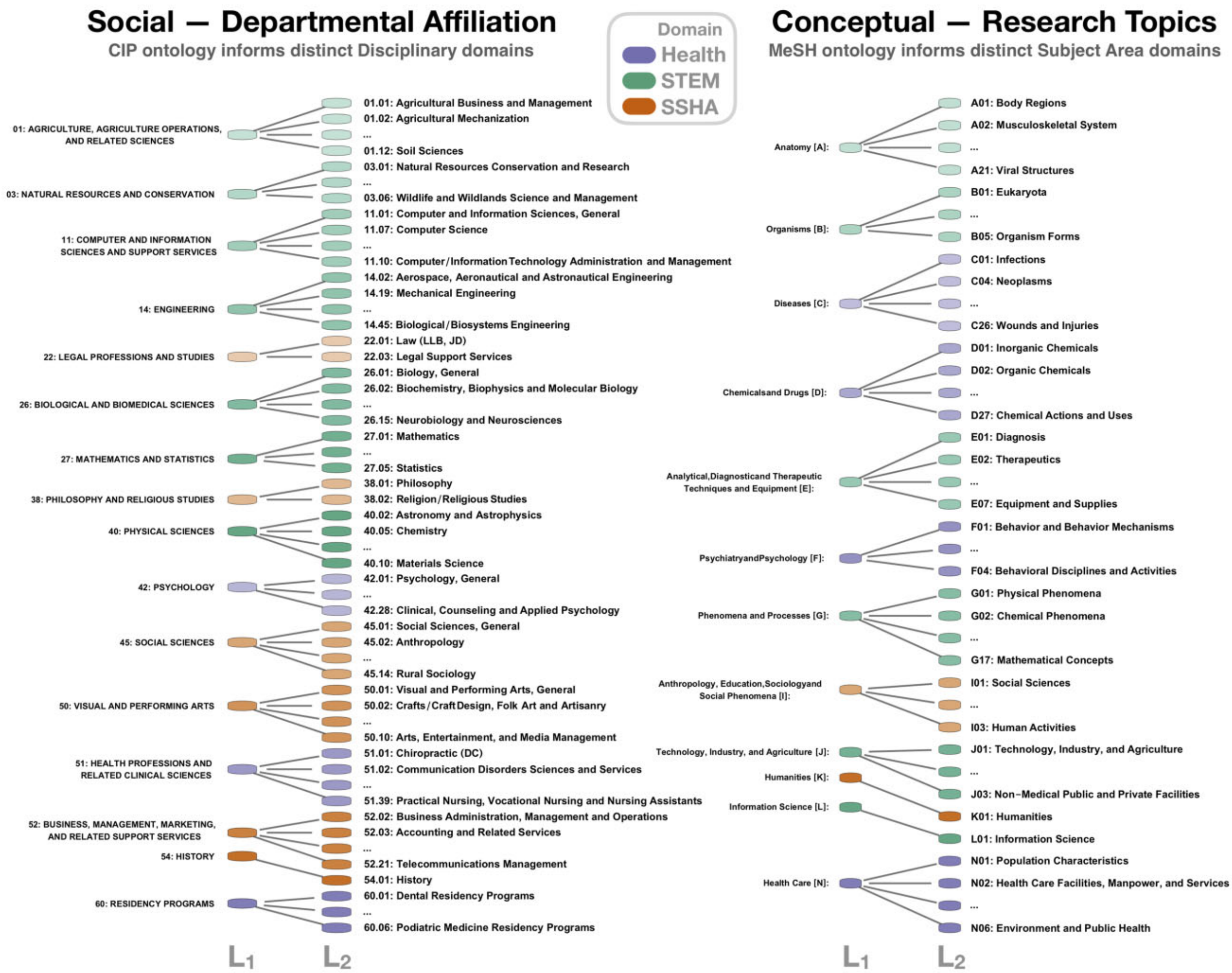

Figure 3. Social and conceptual ontologies for measuring cross-domain convergence. Shown is only a small portion of the (left) CIP ontology maintained by the US National Center for Education Statistics (National Center for Education Statistics 2022); and (right) *Medical Subject Heading (MeSH)* ontology maintained by the US National Library of Medicine (U.S. National Library of Medicine 2022). Ellipses indicate the L_2 categories that are too numerous to show (connoting 1,000 s of CIP and MeSH not shown), and extend each ontology across a broad scope that covers nearly all social and conceptual domains. The entire CIP ontology can be explored here: https://nces.ed.gov/ipeds/cipcode/browse.aspx?y=56. See the Supplementary Appendix regarding the limitations and scope of these ontologies. For each shown entity (ellipses connote 1,000 s of CIP and 30,000 s MeSH not shown), we manually classified the parent (L_1) category according to three distinct 'super-group' domains: Health science (purple); STEM (green); and Social Sciences, Humanities and Arts (orange); variable color tones are provided as visual aid for distinguishing distinct categories at higher branch level cuts. Depending on the convergence resolution being considered, the choice of level cut separates the ontology into various domains. For example, a partition according to the tripartite super-group (L_0) implies that Materials Science and Statistics are neighboring disciplines; however defining boundaries according to L_1 means these two disciplines are considered distinct; and for both L_0 and L_1 partitions, Aerospace and Biological/Biosystems are neighboring Engineering sub-disciplines.

bounded, $0 \leq f_{D,p} < 1$. Mono-domain publications, yielding $\vec{v}_p$ with just a single non-zero element located on the matrix diagonal, correspond to $f_{D,p} = 0$. Contrariwise, in the case of a uniform distribution, when all vector elements having the same value, the measure records the maximum value, $f_{D,p} = (d-1)/(d+1) \approx 1$, where d is the number of distinct domains within the ontology and thus the dimensionality of $\vec{v}_p$.

As formulated, $f_{D,p}$ is a Blau-like measure of both categorical variety and concentration disparity (Harrison and Klein 2007), since by construction the number of distinct domains is fixed by the level cut applied to the hierarchical ontology. As such, $f_{D,p}$ increases as the number of distinct domains represented by p increases; it also increases as the parity in weight values encoded in $\vec{v}_p$ increases. There are various alternative diversity measures employed in the scientometrics of IDR (Stirling 2007; Leydesdorff, Wagner and Bornmann 2018, 2019), the most similar being the 'Stirling Index' Δ_p (Stirling 2007), which requires an ad hoc prescription of a distance d_{ij} between any two categories i and j. By comparison, our method uses the hierarchical ontology to organically define all d_{ij}. While it is neither our objective nor our interest in comparing or establishing the superiority of these various diversity measures, this definition opens the possibility for exploring the utility of these other diversity measures by leveraging the d_{ij} encoded in the ontology.

In summary, we chose the tensor-product formulation of $\boldsymbol{D}_p$ to capture the combinatorial features of convergence. We anticipate that higher-order matrix decomposition methods and measures, such as the distribution of eigenvalues of $\boldsymbol{D}_p$, will reveal new insights into the structure and dynamics of convergence. For example, recent work analyzing $f_{D,p}$

calculated across the entire 21.6 million research articles indexed within PubMed over the period 1970–2018 shows a steady increase in conceptual convergence over the last half century, with wide levels of variation across individual journals likely attributable to the propensity for different scholarly communities to support convergence science (Yang, Pavlidis and Petersen 2023).

HBS research corpus

The broad frontier of HBS is an appropriate testbed for developing this convergence measurement framework given that it represents domain-spanning research in the core biological sciences (physiology of structure, function, and evolution), the behavior and public health sciences, and also relies of advanced medical imaging technologies, as well the cognitive science of intelligence, artificial, and natural. It is also a relevant area to study given several ongoing national funding initiatives such as BRAIN in the USA and the Human Brain Projects in Europe, which are on the order of a billion US$ in total funding size.

To demonstrate the practical application of this framework, we constructed a comprehensive scholar-centric representation of the HBS ecosystem by collecting and merging publication data from Web of Science (WOS), Scopus, and PubMed. The former dataset was used to identify articles associated with the topic field query 'Human Brain' from the WOS Core Collection over the period 1955–2016. This initial search returned 224,201 publication records. From this set we identified the full first and last names of all authors with $\geq$ 5 publications, including their most recent affiliation. To address the name disambiguation problem, we then used the Scopus Author API to identify 9,121 distinct HBS profiles over the period 1945–2018. We manually classified each Scopus Author's affiliation according to 9 CIP groups: (1) Neurosciences, (2) Biology, (3) Psychology, (4) Biotech and Genetics, (5) Medical Specialty, (6) Health Sciences, (7) Pathology and Pharmacology, (8) Engineering and Informatics, and (9) Chemistry, Physics, and Math. The collection of CIP categories across all coauthors thereby define the social dimensions of a given article. Similarly, in order to define the conceptual dimension of HBS research, we matched each Scopus record to its PubMed entry in order to obtain the set of MeSH for each article. The final dataset is comprised of 655,386 research articles systematically classified according to the MeSH and CIP ontologies. For more dataset construction details, including the open dataset (see Petersen et al. 2021; Pavlidis and Zhukov 2022).

To measure each article's research impact through late 2019, we obtained the citation count $c_{p,t}$ for each article p published in year t using the Scopus API. Because nominal citation counts suffer from systematic temporal bias (Petersen et al. 2018), in what follows we use a normalized citation measure denoted by

$$z_{p,t} = (\ln(c_{p,t} + 1) - \mu_t)/\sigma_t, \qquad (2)$$

where $\mu_t \equiv \langle \ln(c_t + 1) \rangle$ is the mean and $\sigma_t \equiv \sigma[\ln(c_t + 1)]$ is the SD of the citation distribution for a given t; we add 1 to $c_{p,t}$ to avoid the divergence of ln 0 associated with un-cited publications—a common method which does not alter the interpretation of results. Consequently, the normalized citation measure z_p is a robust measure that is well-fit by the Normal $N(0,1)$ distribution, independent of t; see Petersen et al. (2021) for a demonstration of this statistical stationarity. Publications with $z_{p,t} > 0$ (respectively, $z_{p,t} \leq 0$) can be collected by year into above-average (respectively, below-average) article groups. The scale of the logarithmic citation distribution σ_t is also relatively stable over the 49-year period 1970–2018 (average and SD value are $\langle \sigma \rangle \pm \text{SD} = 1.24 \pm 0.09$). Hence, in our regression model that follows, we model the dependent variable $Y \equiv z_{p,t}$ and estimate the regression coefficient β_x associated with an independent variable x that ranges between 0 and 1. As elaborated in Petersen et al. (2021), the percent change in citations $c_{p,t}$ associated with the variable x shifting from 0 to 1 is $100\Delta c_p/c_p \approx 100\langle \sigma \rangle \beta_x$.

Results

Evaluating the prevalence of different convergence science modes

This convergence framework facilitates a variety of novel perspectives in the science of science and science policy (Fealing 2011; Fortunato et al. 2018) for understanding how and when convergence emerges, and for also detailing the structural properties of nascent integration interfaces. Consider, for example, patterns of cross-disciplinary collaboration of scholars from two or more originally distinct domains. From this perspective, social convergence is highly dynamic, involving both the entry and exit of scholars into the interface between domains. Such a convergence nexus is seeded by individuals and their social interactions. An example of the former is the cross-disciplinary mobility of a scholar from one domain to another; an example of the latter is the formation of a potent cross-disciplinary collaboration between scholars. Either scenario can give rise to a persistent interface that accelerates the cross-pollination of theory, methods, and culture—a scenario that typifies the emergence of cross-disciplinary collaboration in the Human Genome Project and the role of cross-disciplinary mobility embodied by Dr Eric Lander and several other subsequent bioinformatics leaders (Petersen et al. 2018). Both individual and group-level social convergence modes are critical for addressing complex multi-dimensional problems calling on systems-thinking approaches (Orsatti, Quatraro and Pezzoni 2020; Wanzenböck et al. 2020).

Whereas some interfaces involve just two domains, as in the genomics revolution (Petersen et al. 2018), others may involve multiple domains, as is typical of environmental problems (Petersen, Vincent and Westerling 2019; Arroyave et al. 2021). In particular, Figure 4A shows the emergence of a triple-domain nexus—the convergence of the neuro-biological $\leftrightarrow$ health $\leftrightarrow$ techno-informatic domains—that characterizes the HBS frontier. Structural comparison of cross-disciplinary collaboration networks constructed across two decades indicates the increasing densification at this human brain (HB) science frontier coinciding with the emergence of massive flagship funding programs in the USA, Europe, and Australasia occurring in the period 2009–18 (Petersen et al. 2021). Discrepancies in the configurations of social and conceptual dimensions identify science policy pathways to adjust, incentivize, institutionalize—and in the long run—to accelerate convergence.

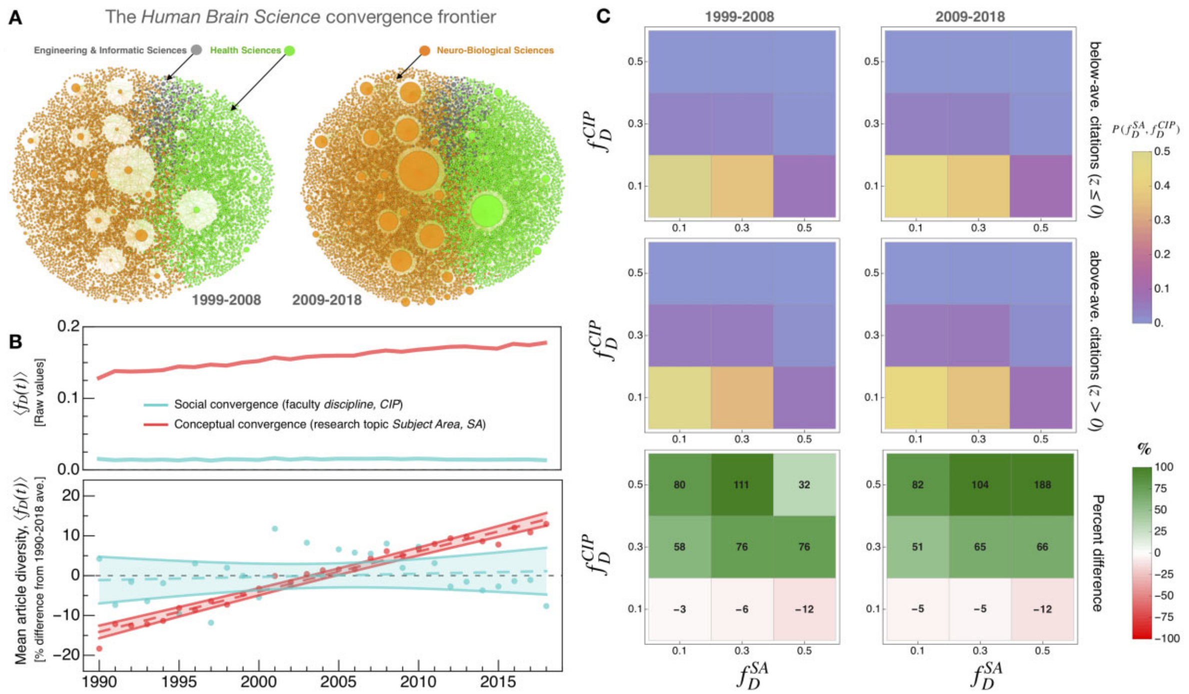

Figure 4. Trends in social and conceptual convergence in the nexus of HBS. (A) Evolution of cross-domain integration at an exemplary convergence nexus—the HBS frontier. Shown is a network visualization of collaboration among ∼9,000 researchers active in brain research (650,000 research articles in total), partitioned across two balanced 10-year intervals; see Petersen et al. (2021) for more details and extensive analysis. With researcher (node) locations fixed and node size proportional to collaboration (link) degree, inter-temporal comparison illustrates the high degree of cross-domain integration mediated by cross-disciplinary collaboration across three distinct L_1-level CIP domains. (B) Convergence is measured at the article level by way of the department affiliation and research topic ontologies illustrated in Figure 3. Each time series in the top panel shows the mean convergence levels, measured according to $f_{D,p}$ defined in Equation (1); social convergence values are substantially smaller than conceptual convergence values, which indicates different rates of cross-domain integration within these dimensions. To convey the trends net of baseline levels, data in the second panel are transformed into units of percent difference from the cross-temporal average value. While disciplinary convergence has fluctuated around its mean value with no significant trend over 1990–18, topical diversity has steadily increased. Data points represent $\langle f_D(t) \rangle$, and dashed line shows the linear trend fit along with 99% confidence interval (social convergence: $R^2 = 0.97$ and linear model P-value $< 10^{-10}$; conceptual convergence: $R^2 = 0.14$; P-value $= 0.54$). Considered together, this dichotomy represents a sub-optimal *convergence shortcut* (Petersen et al. 2021), whereby scholars increasingly tend to integrate concepts without integrating expertise appropriate to the research problem. (C) Joint frequency distribution $P(f_D^{SA}, f_D^{CIP})$ calculated for the same two periods as in (A). The upper (middle) row shows the frequencies of below-average (above-average) cited articles for common bins of width 0.2. In both cases, the majority of articles fall into the bins representing low disciplinary diversity, $f_D^{CIP} \in [0, 0.2]$. The third row of matrices shows the percent difference (listed within each cell) calculated between the matrices for $z > 0$ and $z \le 0$ directly above and for the same period. While difficult to infer from visual comparison of the color gradients, the percent difference matrix illustrates the significantly greater frequencies of larger f_D^{SA} and f_D^{CIP} values encountered in highly cited research. For example, for 2009–18, there is a 108% increased likelihood of observing $f_D^{SA} \in [0.2, 0.4]$ and $f_D^{CIP} \in [0.4, 0.6]$ for above-average relative to below-average cited research.

Figure 4B juxtaposes the average domain-spanning diversity $\langle f_D(t) \rangle$, a measure of convergence within the social and conceptual dimensions, individually. Comparison of historical trends points to different drivers of convergence in each dimension. To emphasize the distinct trends observed for each dimension, we also show $\langle f_D(t) \rangle$ values reported in units of percent difference from the mean value calculated across the entire period. Two distinct patterns emerge, suggesting different challenges associated with effecting cross-domain integration of each type. Whereas disciplinary (SA) convergence has fluctuated around its mean value (with no statistically significant trend), conceptual (CIP) convergence has steadily increased ∼30% over the three-decade period 1990–18 (P-value < 0.0001). This result suggests that it is relatively easier to integrate cross-domain knowledge than to integrate cross-disciplinary expertise, likely owing to coordination costs and other constraints associated with crossing disciplinary and organizational boundaries (Cummings and Kiesler 2005, 2008; Feller 2006; Van Rijnsoever and Hessels 2011; Bromham, Dinnage and Hua 2016). For more on this disparity in social and conceptual integration, and econometric analysis pointing to the perverse role of incentives to rapidly form teams in order to secure funding (see Petersen et al. 2021).

Naturally, the question arises as to which of three convergence modes—research characterized as polymathic convergence only (X_{SA}), cross-discipline only (X_{CIP}), or full convergence ($X_{SA\&CIP}$)—prevails in practice and impact. To address this question, we partitioned the publication data depending on $f_{D,p}^{SA}$, $f_{D,p}^{CIP}$, and z_p and show in Figure 4C their joint frequency distributions. While there is little variation in the joint distribution $P(f_{D,p}^{SA}, f_{D,p}^{CIP})$, aside from the marginal growth of $f_{D,p}^{SA}$ indicated in panel A, comparing above-average ($z > 0$) relative to below-average cited research ($z \le 0$) shows that higher joint convergence values correlate with highly cited research. For more robust econometric analysis (see Petersen et al. 2021), which shows that research featuring full convergence ($X_{SA\&CIP}$, corresponding to research with $f_{D,p}^{SA} > 0$ and $f_{D,p}^{CIP} > 0$) features a 6% citation premium relative to polymathic research (X_{SA}). This differential reflects the additional quality and rigor of research that passes the thresholds of multi-disciplinary evaluation and communication.

Complementary analysis of this HBS dataset provides insights into the mechanism giving rise to this disparity, finding an increasing propensity for teams to purse conceptual convergence without appropriate social convergence—i.e., a *convergence shortcut* (Petersen et al. 2021). This result points to the increasing prevalence of a strategy for rapidly and efficiently competing for large flagship funding opportunities that foregoes the more timely and costly efforts associated with cross-disciplinary team assembly. While expanding beyond one's core expertise, as endowed by the traditionally mono-disciplinary channels of graduate education, largely reflects the innate curiosity at the foundation of scholarship, it also signals the dawn of a new era of autodidactic education by way of open science data, code and tutorials. The theory of expansive learning (Engeström and Sannino 2010) provides understanding for this innate autodidactic propensity, which arises naturally in highly interconnected social systems, and is further supported by cross-pollinating team science.

Evaluating the alignment of social and conceptual dimensions

Convergence is optimally operational when multidisciplinary teams are appropriately aligned with the boundary-spanning target problem, as illustrated in Figure 5A. In effect this means that the strategic assembly of teams should follow *form follows function* design principles. The function of the team should be tailored to the focal subject area of the target problem. However, most challenges are grand in that they are inextricably embedded in a network of contingencies and risk (Helbing 2013), a complex state of dependency that support chain reactions that extend well beyond the source domain, and thereby requires deep understanding pertaining to each of those domains as well. Further exacerbating this issue, different communities of expertise, which in the most ideal case are in agreement as to what is the core problem, may not necessarily be in (or reach in a timely manner) a working level of consensus around which pathway to take, thereby giving rise to 'wicked problems' (Stirling 2010; Arroyave et al. 2021).

The process by which a sustainable convergence nexus emerges is likely akin to the nucleation and growth of stable surfaces in disordered media developed in statistical physics (Krapivsky, Redner and Ben-Naim 2010). Nucleation commences when problem-solving expertise identifies an emerging target problem, forms a local community around some partial dimension of the problem, and then coalesce with other stakeholders at subsequent stages of cross-disciplinary integration in order to avoid eventual disassociation. Analysis of 'wicked' target problems in the environmental sciences (Arroyave et al.

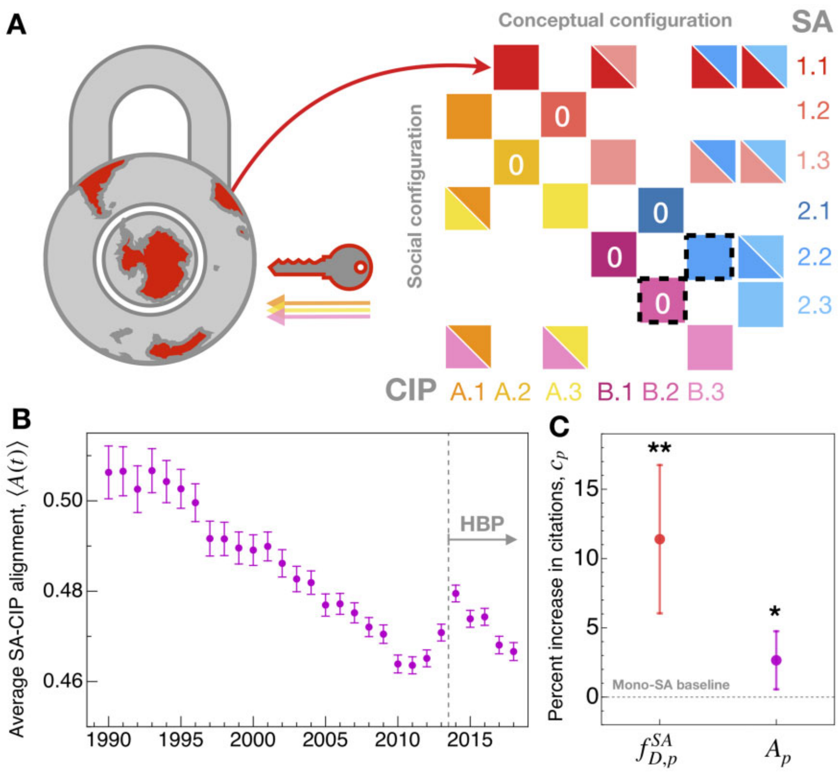

Figure 5. Evaluation and impact of socio-conceptual (CIP-SA) alignment. (A) Schematic of a target problem, e.g. melting polar ice-caps deriving from global warming, which maps onto a particular configuration of SA hypothetically spanning two 'super-group' domains, each featuring three L_2 domains. A particular research team tackling this particular problem can be represented by a social configuration codified by six corresponding CIP (A.1 through B.3). As such, this approach to measuring and evaluating convergence can aid policymakers and principal investigators in designing teams that represent strategic configurations of expertise aimed at specific target problems, which are themselves conceptualized as configurations of core concepts (e.g. established knowledge, methods, and tools). Consistent codification of social and conceptual configurations can help identify candidate pathways for unlocking solutions to grand challenges. The relative composition of the conceptual and social configurations can also identify when teams are not sufficiently aligned with the problem, as indicated by the cells with dashed black borders suggesting that the social configuration is misaligned since there is no expertise ('0' weight in CIP B.2) to match the corresponding dimension SA 2.2 of the target problem. (B) Average social-conceptual alignment $\langle A(t) \rangle$ calculated by year, with error bars indicating the standard error of the mean. (C) Regression coefficients for the two main model variables reported in terms of the percent increase in citations attributable to research featuring full SA convergence ($f^{SA}_{D,p} = 1$) and full alignment of CIP with the SA ($A_p = 1$), measured relative to the mono-disciplinary baseline with $f^{SA}_{D,p} = 0$.

2021) shows that the formation of an initial nucleation seed, consisting of cross-disciplinary leaders that spur subsequent cross-domain integration, can be hampered by the opacity of the underlying problem. Hence, it is likely that direct incubation of nascent interfaces is critical for the synthesis and spin-off of new multi-component sub-disciplines (Bonaccorsi 2008). To foster this engagement and momentum, social coordination should aim to increase alignment between CIP and corresponding SA domains over time.

The continuous evaluation of alignment between activities and objectives is critical to adaptive science policy (Arroyave et al. 2022). To this end, we evaluate the development of SA-CIP alignment using the tripartite nexus of neuro-biological, health, and techno-informatic domains shown in Figure 4A that are guided by the explicit agendas of various HB projects. We measure the degree to which research teams are aligned with the particular slice of the problem they are researching by calculating the inner-product of the normalized count vectors, $A_p \equiv \vec{v}_{\mathrm{SA},p} \cdot \vec{v}_{\mathrm{CIP},p} / (|\vec{v}_{\mathrm{SA},p}||\vec{v}_{\mathrm{CIP},p}|) \in [0, 1]$, with 0 corresponding to misalignment and 1 corresponding to ideal alignment.

Figure 5B shows the trend in average SA-CIP alignment $\langle A(t) \rangle$, which is characterized by a steady decline in alignment since the 1990s which may reflect a natural underlying tendency for increasing misalignment as the scope of HBS grows over time. Notably, there is a sudden alignment increase in the two years prior the launch of various international HBS projects in late 2013, followed by a precipitous decline. The coincidence of this burst provides further indication of the 'convergence shortcut' illustrated in Figure 4B.

To quantify the implications of SA-CIP alignment on research impact, we estimated the coefficients of the following linear regression model,

$$z_{p,q} = \beta_0 + \beta_{\mathrm{SA:CIP}} A_p \; + \; \beta_{\mathrm{SA}} f^{\mathrm{SA}}_{D,p} + \beta_k \ln k_p + \gamma_Y \; + \gamma_{D_j} + \epsilon_{y,D}$$

implemented in STATA 13 using a fixed-effects estimation (xtreg). The covariate k_p measures the number of coauthors, and γ_Y represents fixed effects for publication year to account for idiosyncratic year-specific shocks. To account for unobserved journal-level characteristics associated with prestige, as represented by γ_{D_j}, we calculated the average journal impact $z_{j(p)}$ of the journal j publishing article p, and then grouped journals into deciles $D_j = \in [1, 10]$ according to $z_{j(p)}$. We do not include $f^{\mathrm{CIP}}_{D,p}$ because this would overfit the estimation of $\beta_{\mathrm{SA:CIP}}$ when both $f^{\mathrm{SA}}_{D,p} \approx 1$ and $f^{\mathrm{CIP}}_{D,p} \approx 1$ which guarantees $A_p = 1$.

Figure 5C shows the percent increase in citations associated with our two focal covariates: $100\langle\sigma\rangle\beta_{\mathrm{SA}} = 11.4\%$ ($P = 0.0024$; 95% CI = [6.0, 16.7]) and $100\langle\sigma\rangle\beta_{\mathrm{SA:CIP}} = 2.7\%$ ($P = 0.034$; 95% CI = [0.6,4.7]). Effect sizes are relative to the mono-SA baseline, meaning that on average, an article featuring maximum topical convergence $f^{\mathrm{SA}}_{D,p} = 1$ receives roughly 11.4% more citations than an article with $f^{\mathrm{SA}}_{D,p} = 0$, independent of $f^{\mathrm{CIP}}_{D,p}$, and all other covariates being equal to the average value. Yet if the CIP of the same article are perfectly aligned with the SA (i.e., $A_p = 1$), then the citation premium increases to 14%. See Table 1 for the full list of model estimates.

Discussion

The paradigm of convergence extends well beyond the standard formulation of IDR as diversity of disciplinary components (Nissani 1995; Wagner et al. 2011; Laursen, Motzer and Anderson 2022), which may well arise from spurious mixing, as well as secular trends in the growth of science that supports the spin-off of new hybrid sub-disciplines (Bonaccorsi 2008). Instead, convergence is distinguished from IDR in that it calls for the collaboration of originally distinct domains that strategically identify social and conceptual configurations (a key) that are well-suited to satisfy the constraints defined by the particular target problem and delineated by the overarching mission-oriented agenda (the lock) – as illustrated in Figures 1 and 5A. This distinction is reflected by the first 13 NSF *Convergence Accelerator* challenge areas selected through 2023, each framed around a specific problem nexus calling on a specific configuration of disciplines. Notably, each convergence track is characterized by a set of social, technological, and environmental contingencies that highly constrain the solution space, thereby calling for representative expertise from each convergence domain. Such problems are often deemed 'wicked' in that the communities of problem-solvers, while manifestly potent in terms of their combined capabilities, may nevertheless lack consensus regarding conceptual definitions and candidate solution pathways (Wanzenböck et al. 2020; Arroyave et al. 2021; Grewatsch, Kennedy and Bansal 2021). And while these communication and organizational issues are inherent to IDR, they are likely exacerbated in convergence science.

To this end, we developed a framework for operationalizing the quantitative evaluation of convergence, one that leverages hierarchical ontologies for identifying distinct domains that give rise to potent team configurations (RQ 1–3). We then showcased how this framework can aid in the assessment of progress and outcomes by way of a case study of the HBS frontier (RQ 4–5) to address five research progressive questions (RQs). Regarding RQ4, our empirical analysis highlights the *convergence shortcut* documented more extensively in Petersen et al. (2021), whereby scholars integrate diverse topics without integrating appropriate disciplinary expertise. Such research configurations are likely to be sub-optimal, as high-impact convergence research tends to be high in both topical and disciplinary diversity (see Figure 4). Yet they may be more economical, foregoing the risky and costly factors associated with social capital investment, by instead filling in the expertise gaps by way of expansive learning (Engeström and Sannino 2010) that is a hallmark of cross-disciplinary mobility of individual scholars transitioning from one distinct domain to another (Petersen et al. 2018). Regarding optimal team assembly for convergence (RQ 5), our results robustly demonstrate the added value of SA-CIP alignment when tackling boundary-spanning problems—here identified as a 14% citation premium for well-aligned convergence science (see Figure 5).

There are of course limitations to the proposed framework. From a technical perspective, mapping ontological entities to their locations in the hierarchy is computationally intensive, and certain choices must be made as to how to deal with edge cases, such as entities that by definition are boundary-spanning. Also, the choice of ontology level cut, which identifies what is considered neighboring or distant, is also subjective. This framework parameter thus affects the baseline frequencies of boundary-spanning combinations that makes it challenging to compare results for different level cuts. Moreover, the ontologies are not uniformly available across different research indices, although this is also the case for the

Table 1. Measuring the impact of SA diversity and SA-CIP alignment on citation impact

	Independent variable: $Y = z_p$ (normalized citations)		
Model	(1)	(2)	(3)
A_p	0.0137		0.0214*
	(0.195)		(0.035)
$f^{SA}_{D,p}$		0.0822*	0.0919**
		(0.011)	(0.002)
ln k_p	0.262***	0.260***	0.261***
	(0.000)	(0.000)	(0.000)
Const.	−0.343***	−0.325***	−0.356***
	(0.000)	(0.000)	(0.000)
Year FE, y_p	Y	Y	Y
Journal prestige FE, D_j	Y	Y	Y
N	618,301	618,301	618,301
adj. R^2	0.036	0.036	0.036

P-values are in parentheses. Article-level analysis using hierarchical regression model with year and journal-impact fixed effects estimated using STATA13 with 'xtreg fe vce (robust)' specification, which accounts for unobserved time-independent variables associated with journal prestige (D_j). The units of observation are articles published in period $y_p \in [1990, 2018]$. P-values are shown in parenthesis below each point estimate. The first two columns confirm the robustness of the A_p and $f^{SA}_{D,p}$ coefficients alone, and the third column shows the combined effects which are additive, since an article can have maximum SA diversity ($f^{SA}_{D,p} \approx 1$) and still feature poor SA-CIP alignment quantified by A_p. Note that $f^{CIP}_{D,p}$ is not included in the regression model because this would overfit the model in the case of $f^{SA}_{D,p} = f^{CIP}_{D,p} \approx 1$, which implies $A_p \approx 1$.

* P < 0.05.

** P < 0.01.

*** P < 0.001.

flat classification systems as well. From the perspective of research evaluation practice, there may develop a negative connotation associated with research connoted as 'low diversity' or 'mono-domain', when in reality research of this type is commonly targeting deep problems that are critical and highly valued to longstanding core disciplines. Another issue is how to classify hybrid disciplines that were ahead of their time—e.g., it could be tempting to classify seminal biophysics researchers not as boundary-spanning explorers, but rather as contemporary traditionalists; this issue of backwards compatibility of the ontologies is addressed by MeSH, which records a very rich history of changes to definitions and relationships between entities, but not by the CIP ontology, which has a limited history dating back to the 1980s, with less clarity regarding changes occurring in each decadal update.

In sum, this work addresses the organizational challenges that precede the scientific challenges by providing a practical evaluation framework for strategic team assembly. By comparing the topical domains of the target problem with the disciplinary expertise of the assembled team, this framework has applications to proposal ranking and funded project evaluation, policy design, and onwards to global assessment. We further anticipate that the assembly of convergence teams will soon be enabled by data-algorithmic platforms that can accelerate searching across the full recombinant space of topics and disciplines (Petersen 2022), thereby facilitating high-bandwidth human–machine convergence—the natural next stage of its evolution (Pavlidis, Akleman and Petersen 2022).

Institutionalizing convergence

Effecting convergence can be recast as the social-engineering of strategically designing teams, keeping in mind the challenges to integrating disciplines and epistemology over long distances. As such, to a large degree, many of the logics and incentives that support grass-roots IDR will also support mission-oriented convergence, namely deep consideration for individual and team experience in IDR, propensity for IDR, and emphasis on effective and respectful communication (Cummings and Kiesler 2005, 2008; Barry, Born and Weszkalnys 2008; Van Rijnsoever and Hessels 2011; Orsatti, Quatraro and Pezzoni 2020).

Continued institutional support for convergence will be critical, not only from the national funding bodies from which the paradigm originates (National Research Council 2014), but also within universities and other institutions with research missions. Examples of grass-roots academic convergence include the hybrid fields of chemical biology, astrobiology, and econophysics (Mantegna and Stanley 1999). Whereas the first two were eventually championed by funding agencies (Colón et al. 2008), for example the US NSF and NASA agencies combining agendas with the 'Origin of Life' program, the latter has not reached this critical threshold. Top-down institutional support is increasingly prominent. Two exemplary cases that embody the spirit of 'Academe without borders' are the Santa Fe Institute (New Mexico, USA) and the Copernicus Institute of Sustainable Development (Utrecht University, NL), where resident faculty organize around research themes as opposed to units defined according to traditional disciplines. Other examples of standalone transdisciplinary units (as opposed to collectives serving as secondary affiliations) are the MIT Media Lab, which promotes a transdisciplinary innovation culture that embraces problem-oriented design by promoting cross-sectoral inspiration; and the Management of Complex Systems department at the University of California Merced, which is a standalone university department, wherein no two faculty share a common PhD field.

Yet institutional support for such endeavors comes with obvious human resource challenges, such as how to balance breadth versus depth of disciplinary scope to address both research and instructional objectives. Another tricky problem is how to operationalize standard academic merit and promotion procedures in transdisciplinary units featuring low disciplinary redundancy, which tests the assumptions of effective peer-assessment given the stark cultural, educational, and research productivity differences that exist across disciplines.

One final consideration is the task of establishing traditional concepts of norms, consistency, and continuity in convergent organizational units. By contradistinction, in traditional mono-disciplinary organizational units the minimum required forward momentum can be obtained simply by leaning on commonality. However, achieving commensurate momentum in convergence-oriented units is not a given. Indeed, establishing a mission, vision, and the impetus to achieve them may require additional coordination, and may be especially susceptible to the high levels of turnover in personnel, research agendas, and funding. These and other of social-engineering issues are organizational challenges by their very nature, and only contribute to the overarching burden of identifying strategies for unlocking the social and conceptual dimensions of grand challenges.

Accelerating convergence

Looking forward, we expect to see a maturation of convergence in cases where the subject matter of the research exceeds the apparent disciplinary bounds of the participating researchers. This is the type of 'convergence shortcut' that was found to be sub-optimal in brain research during the 2010s. The reason for the projected reversal of fortunes has to do with the powerful processes unleashed from the ongoing implementation of convergence science policies that establish the overall agenda, objectives, and constraints. Up until now the disciplinary affiliation of researchers characterized relatively accurately their underlying knowledge and expertise. However, as a new generation of PhDs is trained through TDR grants, where groups from various disciplines collaborate with each other, a new breed of scientists will be trained in polymathic identity, culture, and practice. In the medium and long term, this trend is bound to create a growing drift between departmental affiliations and the traditional content of expertise. The senior scientists in the world today who have been trained in a largely mono-disciplinary culture in the 1990s and 2000s, were mostly 'self-taught magicians' when the push for convergence institutionalized in the 2010s. Hence, whenever they attempted to exceed their disciplinary bounds without collaborative support from relevant experts, they were not as effective. This is no longer the case for emerging scientific cohorts, as they are immersed in a mixed scientific culture that has been decades in the making.

Accordingly, we anticipate the demand for polymathic expertise to return to fashion, serving as transversal 'glue' that binds together composite teams, altogether accelerating the paradigm of convergence. These fledgling polymaths will have truly internalized cross-disciplinarity, which will not only round off the team's knowledge, but also be a boon to intra-team communication for exploring new and more cross-sectional frontiers. We expect convergence to be also aided by the increasing use of technology by polymathic research teams, and especially the enlisting of artificial intelligence (AI) for optimizing team assembly, problem and solution identification. Looking even further ahead, collaboration between AI agents endowed with uber-ontologies and mono-disciplinary and polymathic scholars alike, will prove highly beneficial partnerships, as AI is good at navigating through combinations, of which convergence science (itself a combinatorial construct) generates aplenty.

Supplementary data

Supplementary data are available at *Research Evaluation Journal* online.

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Data availability

Data used for Figures 4 and 5 are available through the Open Science Framework repository https://osf.io/d97eu.

Notes

1. The hierarchical MeSH keyword ontology, introduced in what follows, is a backward compatible system, and hence overcomes the issues associated with the entry, exit and modification of entities and their relationships. When new MeSH and MeSH–MeSH relationships enter the ontology (Petersen 2022), these modifications are explicitly encoded within the modified MeSH hierarchy, and automatically manifest among MeSH assigned to individual articles. Historical details of the MeSH ontology are copiously recorded in its official metadata; for more details, see the NLM help video *What do the Dates in MeSH Mean?* Take for example the MeSH for 'COVID-19', which was established in the 1 January 2021 version of MeSH, but presently the first instance of this MeSH in PubMed is for an article from January 2019 (PMID 30501541) reporting on a relevant tele-health counseling experiment. The disciplinary breadth of MeSH is valuable for identifying novel multidisciplinary intersections, such as the MeSH "Congential Abnormalities" and "History, Early Modern 1451-1600" that classify a medical history article on King Richard III (Jones, 1980).
2. To further illustrate this nuanced point, consider articles published in the high-impact journals *Nature*, *PNAS*, and *Science*, which publish groundbreaking research across the engineering, natural, and social sciences. These journals, and hence all articles published by them, are classified by Web of Science as 'Multidisciplinary Sciences' according to the WC (Web of Science Category) field and by Scopus as 'MULT' according to the SUBJAREA field. Consequently, both WC and SUBJAREA fields underrepresent the conceptual diversity of research. Moreover, since all articles published within these journals receive the same WC, there is no way to identify and compare the research topics between individual research articles based upon WC alone. Instead, it is common to infer the research topics of a given article by inspecting the diversity of WC across all articles cited by or citing a given article, i.e. a second-order attribution identified in co-citation analysis. Since multidisciplinary journals are highly cited, such co-citation approaches systematically under-represent the diverse knowledge integrated within both incremental and transformative research. Another issue is WC frequencies are biased according to the parent journal sizes, which predetermine the variation of journal-level classification varieties in a given data sample. Consequently, WC and SUBJAREA provide a limited

proxy for article-level knowledge diversity in settings where multidisciplinary journals are dominant—an increasingly relevant issue associated with the meteoric rise of megajournals, which following their all-encompassing business design, are commonly assigned to the generic multidisciplinary category (Petersen 2019).

3. This feature can be juxtaposed to counting distinct keywords, which would be hard to merge into domains without additional information or assumptions given the ambiguity of flat ontologies. By way of example, consider the article titled 'Reach and grasp by people with tetraplegia using a neurally controlled robotic arm' (Hochberg et al. 2012) representing extremely convergent research, which was assigned 16 unique MeSH keywords by PubMed (https://pubmed.ncbi.nlm.nih.gov/22596161/) that range from 'Arm' and 'Drinking', to 'Man–Machine Systems' and 'Microelectrodes', to 'Motor Cortex' and 'Time Factors', among others. Considered without the hierarchy, this research is defined by 16 equally weighted distinct conceptual categories. However, by leveraging the hierarchy, these 16 MeSH merge onto 10 of the 16 total L_1 domains, with varying weights that are most concentrated in root branches 'Analytical, Diagnostic and Therapeutic Techniques, and Equipment [E]' and 'Phenomena and Processes [G]'. Conversely, a level cut at L_2 yields a representation comprised of 24 L_2 MeSH counts (as some MeSH merge onto multiple categories, depending on the level cut) spanning 17 unique categories, with the most weight falling on the MeSH 'Musculoskeletal and Neural Physiological Phenomena [G11]'.

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