

Scientific and Technological Convergence in AI: From Data-Driven Science to Medical Applications

Fatemeh Naghavi Olya

A Thesis

in

The Department

of

Concordia Institute for Information Systems Engineering

Presented in Partial Fulfillment of the Requirements

for the Degree of

Master of Applied Science (Quality System Engineering) at

Concordia University

Montréal, Québec, Canada

January 2026

© Fatemeh Naghavi Olya, 2026

CONCORDIA UNIVERSITY

School of Graduate Studies

This is to certify that the thesis prepared

By: **Fatemeh Naghavi Olya**

Entitled: **Scientific and Technological Convergence in AI: From Data-Driven Science to Medical Applications**

and submitted in partial fulfillment of the requirements for the degree of

Master of Applied Science (Quality System Engineering)

complies with the regulations of this University and meets the accepted standards with respect to originality and quality.

Signed by the Final Examining Committee:

Dr. A. Hammad Chair

Dr. External Examiner

Dr. N. Bouguila Examiner

Dr. A. Schiffauerova Supervisor

Dr. A. Ebadi Co-supervisor

Approved by

Martin D. Pugh, Chair
Department of Concordia Institute for Information Systems Engineering

2026

Mourad Debbabi, Dean
Faculty of Engineering and Computer Science

Abstract

Scientific and Technological Convergence in AI: From Data-Driven Science to Medical Applications

Fatemeh Naghavi Olya

Scientific and technological convergence—the integration of knowledge, methods, and technologies from diverse domains—is a critical driver of innovation in the modern era. This study examines how scientific convergence drives technological innovation, with a particular emphasis on Artificial Intelligence (AI) as a meta-technology that accelerates interdisciplinary integration. Using 41,556 Canadian AI publications from 2000 to 2023 indexed in Scopus, we map patterns of knowledge convergence through citation networks. Fast-Newman clustering was applied to identify thematic communities via modularity optimization, while BERTopic was used to extract semantic topics within each community. Pathway analysis quantified the temporal evolution of these communities using overlap metrics to capture the dynamics of convergence over time. Our analysis shows that scientific convergence is a structured yet non-linear process driven by meta-technologies such as AI, which serve as cross-disciplinary catalysts. We identified three key patterns that shape new fields, and we observed that four analyzed communities embody a common growth pattern in which interaction with real-world problems enriches methodological knowledge, in tune with the paradigm of “use-inspired” basic research. These results highlight artificial intelligence’s central role in bridging distinct domains, fostering the emergence of new scientific disciplines, and enabling transformative technological developments. The proposed framework offers a data-driven approach for anticipating high-potential interdisciplinary fields, guiding strategic investments, and informing innovation policy in an increasingly interconnected research landscape.

Acknowledgments

I would like to express my sincere gratitude to my supervisors, Dr. Andrea Schiffauerova and Dr. Ashkan Ebadi, for their invaluable advice, continuous support, consistent encouragement, and patience throughout my Master's studies. I would also like to take this opportunity to thank my parents and brother for their belief in my abilities and unconditional support. Without their understanding and encouragement over the past two years, completing my studies would have been impossible. Lastly, to my supportive friends who have always believed in me and provided guidance: thank you.

Contents

List of Figures	viii
List of Tables	x
1 Introduction	1
2 Literature Review	4
2.1 Convergence and Divergence of Knowledge Domains	4
2.2 AI as a Catalyst for Technological Convergence	6
2.2.1 AI in Healthcare	7
2.2.2 AI in Finance	7
2.2.3 AI in Transportation	8
2.2.4 AI in Environment	8
2.2.5 AI in Education	9
2.2.6 Canada's Strategic Position in AI Convergence	9
2.2.7 Challenges and Future Trends in AI-Driven Convergence	11
2.3 Methodological Approaches for Studying Convergence	13
2.3.1 Qualitative Approaches	13
2.3.2 Quantitative Approaches	14
2.3.3 Network-Based Indicators	16
2.3.4 Hybrid and Emerging Methodologies	17
2.4 Network and Semantic Analysis as the Primary Lens	19

2.4.1	Future Directions: Predictive Convergence Mapping and Policy	20
3	Data	22
3.1	Data Collection and Filtering	22
3.2	Data Preprocessing	23
4	Methodology	24
4.1	Citation Network Creation	25
4.2	Newman Topology Clustering	25
4.3	Topic Modeling	27
4.4	Topic Label Generation	27
4.5	Topic Quality Evaluation	28
4.6	Convergence Cluster Identification and Pathway Analysis	29
5	Results	31
5.1	Convergence Mechanism	31
5.1.1	Generative Convergence Pattern	31
5.1.2	Transformative Convergence Pattern	32
5.1.3	Divergence Pattern	34
5.2	Pivotal Community Dynamics and Pathway Insights	36
5.2.1	Game Theory	37
5.2.2	Medical Imaging	41
5.2.3	Data Analytics	47
5.2.4	Quantum Machine Learning	51
6	Conclusion	55
7	Limitations and Future Work	57
	Appendix A Fast-Newman Clustering Results	59

Appendix B Detailed Thematic Evolution and Keywords	61
B.1 Thematic Data for Communities Interacting with Community 15	61
B.2 Thematic Data for Communities Interacting with Community 5	69
B.3 Thematic Data for Communities Interacting with Community 41	82
B.4 Thematic Data for Communities Interacting with Community 1160	92
Appendix C Community Network Visualizations and Node Mapping	98
C.1 Network Structure and Node Inventory for Community 15	98
C.2 Network Structure and Node Inventory for Community 5	101
C.3 Network Structure and Node Inventory for Community 41	104
C.4 Network Structure and Node Inventory for Community 1160	106
Bibliography	109

List of Figures

Figure 1.1	Illustration of the scientific knowledge convergence process, adapted from Zhou, Dong, Kong, and Liu (2019).	3
Figure 3.1	Annual distribution of publications by document type in the dataset ($n = 41,556$).	23
Figure 4.1	Overview of the high-level conceptual flow in the analytical pipeline.	24
Figure 5.1	Sample paper citation networks demonstrating the convergence of two fields and the emergence of a new field: Community 341 (blue) + Community 481 (red) → Community 888 (green).	33
Figure 5.2	Sample paper citation networks demonstrating the transformative convergence pattern: Community 41 (blue) + Community 839 (red) → New Community 41 + Community 839.	35
Figure 5.3	Sample paper citation networks demonstrating the divergence pattern: Community 5 (red) diverged, followed by transformative convergence with Community 235 (green) and generative convergence with Community 213 (blue), resulting in an evolved Community 5 (red) and a new specialized Community 316 (black) in 2006.	36
Figure 5.4	Trajectory of Community 15 from 2000 to 2008.	37
Figure 5.5	Trajectory of Community 15 from 2008 to 2016.	38
Figure 5.6	Trajectory of Community 15 from 2016 to 2023.	39
Figure 5.7	Temporal Network of Key Research Themes in Community 15: Labels in red and Years in green (2000–2023)	40
Figure 5.8	Trajectory of Community 5 from 2000 to 2008.	42

Figure 5.9 Trajectory of Community 5 from 2008 to 2016.	43
Figure 5.10 Trajectory of Community 5 from 2016 to 2023.	45
Figure 5.11 Temporal Network of Key Research Themes in Community 5: Labels in red and Years in green (2000–2023)	46
Figure 5.12 Trajectory of Community 41 from 2000 to 2008.	47
Figure 5.13 Trajectory of Community 41 from 2008 to 2016.	49
Figure 5.14 Trajectory of Community 41 from 2016 to 2023.	49
Figure 5.15 Temporal Network of Key Research Themes in Community 41: Labels in red and Years in green (2000–2023)	50
Figure 5.16 Trajectory of Community 1160 from 2008 to 2016.	51
Figure 5.17 Trajectory of Community 1160 from 2016 to 2023.	52
Figure 5.18 Temporal Network of Key Research Themes in Community 1160: Labels in red and Years in green (2000–2023)	53

List of Tables

Table A.1	Table of Communities Detected by FN Each Cumulative Year	59
Table B.1	Community 15: Thematic Evolution of Key Communities. Note: The column Year indicates the first year the respective community was detected in the cumulative network or the first year it was recorded as being involved in a convergence/divergence event with Community 15.	61
Table B.2	Community 5: Thematic Evolution of Key Communities. Note: The column Year indicates the first year the respective community was detected in the cumulative network or the first year it was recorded as being involved in a convergence/divergence event with Community 5.	69
Table B.3	Community 41: Thematic Evolution of Key Communities. Note: The column Year indicates the first year the respective community was detected in the cumulative network or the first year it was recorded as being involved in a convergence/divergence event with Community 41.	82
Table B.4	Community 41: Thematic Evolution of Key Communities. Note: The column Year indicates the first year the respective community was detected in the cumulative network or the first year it was recorded as being involved in a convergence/divergence event with Community 41.	92
Table C.1	Community 15: Node-Label Mapping Table (54 Unique Keywords). This table lists the node identifier and the corresponding keyword/theme. See Fig. 5.7 for the full network visualization.	98

Table C.2	Community 5: Node-Label Mapping Table (63 Unique Keywords). This table lists the node identifier and the corresponding keyword/theme. See Fig. 5.11 for the full network visualization.	101
Table C.3	Community 41: Node-Label Mapping Table (40 Unique Keywords). This table lists the node identifier and the corresponding keyword/theme. See Fig. 5.15 for the full network visualization.	104
Table C.4	Community 1160: Node-Label Mapping Table (40 Unique Keywords). This table lists the node identifier and the corresponding keyword/theme. See Fig. 5.18 for the full network visualization.	106

Chapter 1

Introduction

In recent years, the convergence of scientific knowledge across different disciplines and technological fields has become increasingly prevalent, leading to the development of new technologies [Zhou et al. \(2019\)](#). This convergence process involves synthesizing insights, theories, and methodologies from diverse domains to facilitate advancements that would be impossible within the confines of a single field [Roco \(2016\)](#). Scientific convergence provides the foundation for technological convergence, which leads to the creation and invention of new advanced technologies [Roco and Bainbridge \(2002\)](#). Once these innovations and technologies come into existence, consumers and businesses strive to acquire them in order to be part of this movement. Ultimately, such convergence may give rise to an entirely new industry [Bainbridge and Roco \(2016\)](#). Researchers indicate that technological convergence unfolds in two stages: an incubation phase marked by rapid knowledge exchange, followed by a stable development phase where new fields become established [Zhou et al. \(2019\)](#). This historical progression underscores the role of scientific convergence as a catalyst for technological innovation. Analyzing scientific knowledge convergence is crucial, as it provides the foundational insights needed to predict emerging technological paradigms [Pedota, Grilli, and Piscitello \(2021\)](#). As global economies increasingly prioritize innovation-driven growth—including in Canada, where Artificial Intelligence (AI) innovation is supported by strategic investments like [CIFAR for Advanced Research \(2017\)](#)—understanding the dynamics of scientific convergence enables policymakers and organizations to identify high-potential interdisciplinary fields early in their

development [Zucker and Darby \(2009\)](#). For instance, the convergence of nanotechnology, biotechnology, information technology, and cognitive science (often abbreviated as NBIC convergence) has exemplified this process. In the early 2000s, scientific insights from physics and materials science (nanotechnology) merged with biological principles from genetics and molecular biology (biotechnology), computational algorithms from computer science (information technology), and neural modeling from psychology and neuroscience (cognitive science). This fusion laid the groundwork for new technologies such as targeted drug delivery systems using nanoparticles, bioinformatic tools for genome sequencing, and brain-computer interfaces for enhanced human cognition [Roco and Bainbridge \(2002\)](#). These technologies spurred further innovations, including CRISPR-based gene editing enhanced by AI-driven data analysis and nanoscale sensors for real-time health monitoring. As a result, entirely new industries emerged, such as personalized medicine and neurotechnology sectors, which have created novel jobs. By studying scientific convergence, stakeholders can align research investments with market demands and technological frontiers, fostering sustainable economic development [Cattaneo \(2014\)](#). Additionally, for organizations, leveraging insights from scientific convergence improves strategic decision-making, accelerates innovation cycles, and strengthens competitive positioning in rapidly evolving industries [Ebadi, Auger, and Gauthier \(2022\)](#). As illustrated in Fig. 1.1, one form of scientific knowledge convergence involves integrating two fields (denoted as A and B) to create a new discipline (C), while the original fields (A and B) continue to function independently. The framework presented here employs citation networks of academic papers—extending traditional bibliometric approaches—to map and analyze different forms of knowledge convergence, specifically focusing on the “ $A + B = A + B + C$ ” model. By tracing the integration of insights and methodologies from distinct domains, this approach highlights the dynamic interplay that drives the formation of new scientific fields and technological innovations. This quantitative lens allows for the objective identification of bridging publications that significantly accelerate the formation of the new converged field. By mapping citation networks, this thesis examines the ways in which new fields and innovations develop from the combination of established knowledge domains. This work is motivated by the need to anticipate and guide the development of transformative technologies that have the potential to reshape industries and societies. In Canada—as a key case study—understanding these dynamics is particularly important. By

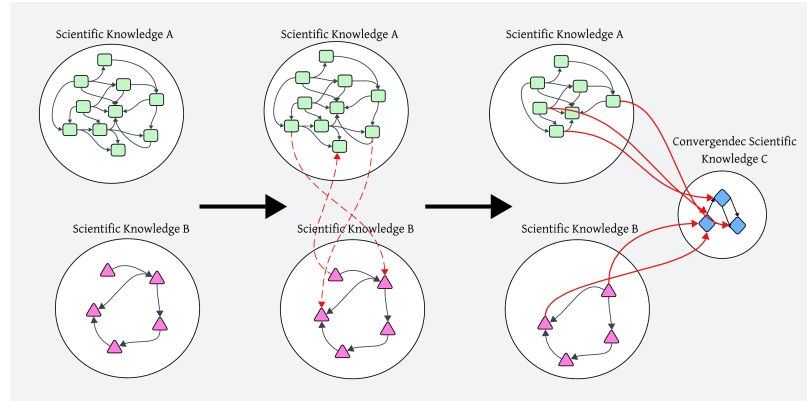


Figure 1.1: Illustration of the scientific knowledge convergence process, adapted from [Zhou et al. \(2019\)](#).

identifying high-potential interdisciplinary fields, the research aims to provide actionable insights for policymakers, organizations, and researchers to strategically align resources, foster innovation, and ensure sustainable economic and social benefits in a rapidly evolving technological landscape. This thesis goes beyond the qualitative description of the process of convergence and instead creates a quantitative model to understand the underlying mechanisms. It proposes a new way to analyze how knowledge integration occurs, with the goal of developing a framework that provides a data-driven method for anticipating high-potential interdisciplinary fields. To achieve this objective, our research is guided by the following fundamental questions:

- (1) What are the key factors that drive the emergence of new disciplines and technologies from the integration of existing knowledge?
- (2) What distinct patterns characterize the processes of scientific convergence?
- (3) How can the dynamics of scientific convergence be used to predict and identify emerging interdisciplinary fields with high innovation potential?

The structure of this thesis is organized as follows: Chapter 2 reviews the related works. Chapter 3, Data, provides a detailed description of the data. Chapter 4, Methodology, presents the techniques employed in this thesis. Chapter 5 outlines the research findings. These findings are discussed, and conclusions are drawn in Chapter 6. Lastly, Chapter 7 addresses the research limitations and suggests directions for future research.

Chapter 2

Literature Review

In this chapter, we review the relevant literature in two main sections, building on the evolving landscape of interdisciplinary research where knowledge boundaries are continually reshaped [Tobi and Kampen \(2018\)](#). First, we discuss the convergence and divergence of knowledge domains, viewing divergence as a complementary dynamic, and analyze the role of AI as a primary catalyst in this process, especially in Canada. Second, we review the methodological approaches for studying convergence, from qualitative foresight techniques to quantitative bibliometric methods, with a specific focus on network-based indicators and hybrid methods that form the foundation for this thesis.

2.1 Convergence and Divergence of Knowledge Domains

The convergence and divergence of fields are fundamental processes in technological development, each uniquely influencing economic and social structures [Skott \(1999\)](#). [Rosenberg \(1963\)](#) was the first researcher to introduce technology convergence as “technological convergence” and suggested that technology convergence is the process of the manufacturing know-how in different industries relying on the same technique. He argues that we need to analyze technological convergence to understand how shared technical problems across diverse industries led to development of new skills and techniques [Rosenberg \(1963\)](#). The concept of technological convergence has evolved since Rosenberg’s work. More recently, studies emphasize “convergence science” as

a multidisciplinary approach to weave different knowledge into solutions for global challenges. These challenges act as catalysts for the adoption of convergence science, compelling researchers to go beyond traditional disciplinary boundaries and integrate diverse knowledge systems. As [Ivanov et al. \(2024\)](#) demonstrate in the Arctic context, the synergistic pressures of climate change and industrialization necessitate holistic, system-level approaches that link social, ecological, and engineering perspectives to understand and mitigate cascading impacts. Similarly, [Moran et al. \(2022\)](#) illustrate how energy poverty and environmental degradation in off-grid Amazonian communities require convergent collaboration among engineers, social scientists, and local stakeholders to co-design sustainable and just energy solutions. Furthermore, [Sundstrom et al. \(2023\)](#) argue that emergent phenomena like zoonotic disease spillovers (events where diseases transmit from animals to humans) and climate-induced regime shifts are unpredictable. This requires integrating panarchy theory with convergence research to better anticipate, prepare for, and respond to systemic surprises. These works underline how the scale, and urgency of modern global challenges accelerate the movement toward convergence science as a necessary paradigm to build resilience and enable effective problem-solving. This urgency and the demand for holistic solutions, driven by global challenges, directly contribute to a corresponding mechanism within the academic [Hall, Stipelman, Vogel, and Stokols \(2017\)](#). This phenomenon appears as an epistemological blending of concepts and methodologies within the academic literature itself. As distinct fields mature, their internal research topics often expand outward, creating shared conceptual frameworks that bridge disciplines [Porter and Rafols \(2009\)](#). For example, the ubiquity of data-intensive methods has acted as a transversal force, driving the research topics of computer science to converge with those of the natural and social sciences to create hybrid domains [Hey, Tansley, Tolle, et al. \(2009\)](#). This granular convergence is often quantifiable through bibliometric analysis and science mapping, where the co-occurrence of keywords from previously separate domains signals the structural emergence of new sub-disciplines [Chen \(2017\)](#). The convergence of research topics thus provides the foundational mechanism by which the broader “convergence science” can operate, transforming abstract multidisciplinary goals into tangible methodological realities.

Conversely, divergence highlights the distinct paths technologies may take, shaped by cultural, economic, and political factors [Vieira, Ouriques, and Pádua dos Santos \(2023\)](#). While convergence

fosters integration, divergence often arises from regulatory heterogeneity, as in biotechnology where varying risk assessments across countries hinder global alignment [Trump et al. \(2023\)](#). The history of scientific divergence reflects a complex interplay between specialization and the formation of distinct disciplines. This trend became particularly evident from the 19th century onward, representing a major shift as the emergence of social sciences challenged traditional humanities, resulting in clear divisions among fields [Bouterse and Karstens \(2015\)](#). The evolution of scientific knowledge has always alternated between periods of divergence, marked by specialization, and convergence, where interdisciplinary collaboration thrives [Goodchild \(2020\)](#). Divergence serves a vital function; it enhances specialization, allowing for the deep exploration of specific areas and leading to breakthroughs that may not occur in more integrated environments [Roco \(2016\)](#). Specialized research contributes to a richer understanding of complex issues, as seen in the evolution of translation factors in biology [Fer, McGrath, Guy, Hockenberry, and Kaçar \(2022\)](#). In modern academic areas, as disciplines mature, researchers often focus on increasingly narrower topics, leading to a temporary lack of interaction between fields [Goodchild \(2020\)](#). This process is crucial because it generates the novel, highly specific knowledge that is later required for productive integration. The dynamic interplay between divergence and convergence thus forms the core engine of scientific evolution. Divergence, as a mechanism of specialization and separation, provides the high-quality components, while convergence, as a mechanism of integration and synthesis, recombines these components to create new systems. This dynamic interplay, which can be explored methodologically using the abductive method to combine diverse perspectives [Guilarte \(2019\)](#), ultimately drives technological advancements [Li \(2024\)](#).

2.2 AI as a Catalyst for Technological Convergence

Scholars argue that economic history advances through distinct structural surges, each driven by a core transformation in production [Perez \(2002\)](#). While earlier industrial revolutions focused on the mechanization of physical power, the recent digital era established a foundation of global connectivity and data generation [Schwab \(2016\)](#). However, the accumulation of this data eventually exceeded the capacity of standard computational methods to handle it, requiring a shift from basic

information processing to intelligent adaptation [Brynjolfsson and McAfee \(2014\)](#). This transition forms the mature phase of the digital revolution, with AI at its core. As a meta-technology, AI stands out for its ability to enhance and extend the impact of other innovations [Hötte, Tarannum, Verendel, and Bennett \(2022\)](#). AI-powered systems, in contrast to domain-specific tools, have the ability to learn, adapt, and generate insights across various contexts, leading to breakthroughs in areas ranging from predictive supply chain management [Kagalwala, Radhakrishnan, Mohammed, Kothinti, and Kulkarni \(2025\)](#) to real-time language translation [X. Liu et al. \(2024\)](#). This adaptability positions AI as a catalyst for convergence, seamlessly integrating with fields such as robotics [Soori, Arezoo, and Dastres \(2023\)](#), healthcare [Song et al. \(2023\)](#), and finance [J. Liu \(2024\)](#), to name a few, and generating multiplicative effects that redefine the technological boundaries.

2.2.1 AI in Healthcare

In the healthcare domain, AI acts as a transformative force, particularly within medical diagnostics and disease prediction where algorithms frequently achieve performance parity with human experts [Song et al. \(2023\)](#); [Usmani and Usmani \(2023\)](#). In this respect, Deep Learning (DL) architectures, especially convolutional neural networks (CNNs), have proved critical, ensuring high efficacy in the early detection of life-threatening conditions like lung and breast cancers [Furizal, Ma'arif, and Rifaldi \(2023\)](#). Beyond diagnostics, these technologies facilitate a shift toward predictive patient care and system optimization, such as identifying at-risk populations to significantly reduce hospital readmission rates [Wan \(2023\)](#).

2.2.2 AI in Finance

Another field that has seen significant integration with AI is finance, where these technologies drive both operational efficiency and enhanced risk management. For instance, AI techniques have substantially improved financial forecasting and budgeting by analyzing historical data to adapt dynamically to market changes, resulting in higher predictive accuracy and optimized resource allocation [Jain and Kulkarni \(2023\)](#). This predictive capability is central to algorithmic trading, where DL models are used to anticipate market shifts and execute high-frequency transactions with precision [Bahoo, Cucculelli, Goga, and Mondolo \(2024\)](#). Furthermore, financial institutions are increasingly

adopting DL algorithms for crucial security functions like fraud detection, while also streamlining processes such as customer onboarding and personalized service delivery. This dual application not only strengthens institutional security but also significantly improves the overall customer experience [Kumar \(2024\)](#).

2.2.3 AI in Transportation

The merging of AI with the transportation sector is fundamentally revolutionizing mobility through both autonomous systems and operational optimization. This is a clear example of technological convergence, where specialized components like LiDAR, radar, high-definition mapping, and deep learning algorithms are synthesized to create a new functional system [Zade, Gawande, Verma, and Gundewar \(2024\)](#). AI enables autonomous vehicles (AVs) to achieve real-time environmental interpretation by leveraging advanced technologies such as computer vision and sensor fusion, which is critical for complex decision-making and enhancing safety [Zade et al. \(2024\)](#). Furthermore, AI extends beyond passenger mobility to logistics and freight management, where machine learning models optimize routes, predict maintenance failures, and manage complex supply chain flows, significantly increasing efficiency across the entire transit network [Richey Jr, Chowdhury, Davis-Sramek, Giannakis, and Dwivedi \(2023\)](#).

2.2.4 AI in Environment

In environmental science, AI serves as a vital convergence point for geospatial data and computational modeling, driving advancements in the analysis of vast remote sensing datasets. Sophisticated ML techniques, including Neural Networks, Support Vector Machines (SVM), and Gated Recurrent Units (GRU), are employed to process satellite and aerial imagery, consistently outperforming conventional statistical models in predictive tasks [Suhana and Karthiga \(2024\)](#). This integration enhances the interpretation of complex environmental phenomena, significantly improving the accuracy of assessments related to land cover classification, vegetation health monitoring, and the early identification of climate anomalies [Alkhayyat et al. \(2024\)](#); [Loganathan et al. \(2025\)](#).

2.2.5 AI in Education

In Education, AI is transforming instruction by facilitating personalized learning (PL), which tailors educational experiences to individual learners' needs. These AI technologies enable adaptive learning systems that customize content delivery, pace, and feedback based on individual student profiles, thereby enhancing engagement and academic performance [Ismail, Ali, and Ashour \(2025\)](#). Platforms utilizing these systems have demonstrated improvements in both student retention and performance metrics [Q. Zhang \(2024\)](#). Moreover, AI extends its application to administrative and institutional efficiency, automating tasks such as grading, scheduling, and identifying high-risk students, allowing educators to dedicate more time to pedagogical strategy [X. Liu, Li, and Liu \(2025\)](#).

These applications clearly demonstrate AI's distinct role as a convergence catalyst. What sets AI apart from earlier general-purpose technologies (GPTs) is its cognitive generality [Johnson et al. \(2025\)](#). Unlike electricity or computing, which primarily amplified physical or computational capacity, AI is uniquely capable of ingesting complex, unstructured data, extracting latent patterns, and exporting those patterns into unrelated domains. The same foundational transformer architecture, for example, now powers advanced language models [Vaswani et al. \(2017\)](#) and predictive scientific applications like protein folding [Jumper et al. \(2021\)](#).

Recognizing AI's significant transformative potential, countries worldwide have launched strategic initiatives to achieve leadership in AI research and implementation. In this context, examining Canada's distinctive position is essential for evaluating the effectiveness of its national strategy in promoting cross-sectoral integration and sustaining global competitiveness.

2.2.6 Canada's Strategic Position in AI Convergence

Canada has established itself as a global leader in AI, a position rooted in significant government investment, strategic policy frameworks, and the broad integration of AI technologies across industries [Cockburn, Henderson, Stern, et al. \(2018\)](#); [for Advanced Research \(2017\)](#). The Pan-Canadian AI Strategy [Department of Finance Canada \(2017\)](#), launched in 2017, allocated substantial funds to AI research with the explicit aim of advancing research, development, and the retention of qualified professionals, thereby reinforcing Canada's position as a leader in AI governance and innovation

[Hachkevych \(2024\)](#). Canada's policy frameworks place strong emphasis on the ethical use of AI, addressing ethical challenges and social impacts to ensure public safety and trust [Andrey, Masoodi, Kwok, and Côté \(2023\)](#); [Gaon and Stedman \(2018\)](#). This strategy also seeks to integrate AI into public policy, improving services in key sectors such as healthcare and national security [Gaon and Stedman \(2018\)](#). Canada's research hubs are essential to this innovation ecosystem, as they encourage crucial cooperation between government, business, and academia, which accelerates scientific discoveries and the development of practical solutions [Attard-Frost, Brandusescu, and Lyons \(2024a\)](#). The economic adoption of AI among Canadian businesses has accelerated significantly year-over-year, demonstrating rapid growth in business AI implementation [Bryan, Sood, and Johnston \(2025\)](#). This technological integration has particularly flourished in information and cultural industries, where AI applications such as text analytics, computer vision, and natural language processing are driving operational efficiencies and innovation [Bryan et al. \(2025\)](#). The workforce implications are equally significant. A substantial portion of the Canadian workforce is now employed in sectors classified as having high AI exposure, with management and business-related occupations showing particularly high rates of technical integration [Larnder et al. \(2024\)](#). Notably, the adoption of AI has not resulted in widespread job displacement; rather, the vast majority of businesses report no change to their number of employees after adopting AI technologies, while simultaneously developing new workflows and operational practices that enhance productivity [Bryan et al. \(2025\)](#). Furthermore, this robust integration aligns Canada's professional workforce characteristics closely with international patterns, positioning Canada as a competitive player in the global AI landscape [Larnder et al. \(2024\)](#).

In healthcare, Canada remains the only nation to have launched a comprehensive national AI strategy from the outset, a move that has accelerated the ethical adoption of medical AI nationwide [Kocabas, Bilgic, Gorgy, and Harley \(2021\)](#). Systematic and narrative reviews report improved diagnostic accuracy, enhanced predictive performance, reduced readmissions, and expanded access possibilities from AI applications in Canadian healthcare [Da Silva, Flood, and Herder \(2022\)](#); [Kocabas et al. \(2021\)](#). At the national level, the Canadian Institute for Health Information (CIHI) has articulated a formal AI strategy to modernize operations and embed responsible AI principles across public health systems [Paramaraj et al. \(2025\)](#). This strategic commitment has catalyzed measurable

improvements across multiple clinical domains.

- **Medical Imaging:** The Canadian Association of Radiologists has documented the transformative potential of AI in medical imaging through their dedicated AI working group and white paper, outlining expected workflow and quality gains [Tang et al. \(2018\)](#).
- **Diagnostic Performance:** Research conducted in leading Canadian academic hospitals has revealed impressive diagnostic performance metrics, with AI systems achieving detection sensitivity and classification accuracy comparable to human experts in areas such as diabetic retinopathy and skin cancer [Shah \(2024\)](#).
- **Clinical Reliability:** AI-driven treatment recommendations have demonstrated substantial agreement with expert oncologists, validating the technology's clinical reliability [Shah \(2024\)](#).
- **Operational Benefits:** Beyond diagnostic accuracy, AI integration has yielded significant operational improvements, with AI-enabled wearable interventions associated with significant reductions in hospital readmissions for chronic disease management [Shah \(2024\)](#).

Canadian metropolitan research hubs in Toronto, Montreal, and Vancouver are leading AI research outputs and hospital deployments, positioning Canada at the forefront of healthcare AI implementation [Hakim et al. \(2020\)](#). These advances underscore how Canada's early, comprehensive national AI strategy has translated into measurable clinical and operational benefits.

2.2.7 Challenges and Future Trends in AI-Driven Convergence

The rapid integration of AI across Canadian industry and government, while transformative, introduces some challenges that must be addressed to ensure responsible convergence. Concurrently, emerging technological fusions are shaping the next generation of AI-driven capabilities [Patil, Yadav, and Pandey \(2024\)](#). The risks inherent to AI deployment primarily emerge where digital algorithms intersect with high-stakes human systems. The pervasive integration of AI into high-stakes decision-making, from finance and credit to judicial and healthcare systems, raises significant concerns about algorithmic bias. If AI models are trained on historical data reflecting existing societal

or systemic prejudices, their deployment can perpetuate or even amplify inequalities and health disparities across the population [Agnes and Special \(2025\)](#); [Aquino et al. \(2025\)](#). This lack of fairness directly impedes the responsible convergence of AI with established social structures. Moreover, A major barrier to deep integration, particularly in regulated professional fields, is the challenge of explainability and transparency. The "black box" characteristic of many sophisticated machine learning algorithms makes it difficult to ascertain how a decision was reached. In critical sectors like medicine or financial services, where accountability is paramount, the lack of interpretability hinders trust and limits the successful convergence of AI with human oversight structures [Aquino et al. \(2025\)](#); [London \(2019\)](#). The fusion of AI capabilities with tasks once considered exclusively human, particularly complex cognitive and knowledge work, is driving a profound transformation of the workforce [Faluyi \(2025\)](#). This convergence necessitates a massive societal shift toward upskilling and reskilling. The focus is increasingly on fostering skills that complement machine capabilities, such as critical thinking, creativity, emotional intelligence, and complex problem-solving, rather than competing directly with automated systems [Brandao \(2025\)](#). Emerging technological trends illustrate the continued evolution of AI by seeking convergence with other powerful fields. The most significant new frontier is the convergence of AI with quantum computing, giving rise to Quantum Machine Learning (QML). This approach integrates fundamental quantum phenomena, like superposition and entanglement, with classical AI models to create hybrid quantum-classical workflows [Illésová et al. \(2025\)](#); [Sethi \(2025\)](#). This technological fusion promises the ability to solve optimization and pattern recognition problems that are currently intractable for classical supercomputers. QML is anticipated to accelerate breakthroughs in highly complex, data-intensive domains such as drug discovery, molecular simulation, financial risk modeling, and advanced materials science [Duong \(2024\)](#). Another key direction of convergence is the fusion of artificial intelligence with robotics, leading to the field of Physical AI. This represents the shift of generalist digital intelligence into the physical world. Advanced Vision-Language-Action (VLA) models are now being developed to directly control robots, enabling systems to extend their reasoning capabilities to handle unstructured, dynamic, real-world tasks with greater dexterity and semantic understanding [Team et al. \(2025\)](#); [Thakur et al. \(2025\)](#). This convergence of software intelligence with physical embodiment fundamentally redefines the scope of automation and autonomous systems.

2.3 Methodological Approaches for Studying Convergence

In this section, we review the methodological approaches for studying convergence.

2.3.1 Qualitative Approaches

The convergence of scientific knowledge has been examined from multiple perspectives. Some studies have employed qualitative approaches, such as the Delphi method [Dalkey and Helmer \(1963\)](#). This technique provides a structured framework for collecting expert opinions, which is essential to evaluate technologies with unpredictable futures [Aichholzer \(2009\)](#). [Arumugam, Ng, and Thambiratnam \(2023\)](#) utilized the Delphi technique, combined with a case study approach focused on Malaysia's nanotechnology, to gather expert opinions and achieve consensus on the development and convergence of innovation systems. Despite its effectiveness in technological foresight, the Delphi method has its limitations, including being time-intensive and requiring careful crafting of statements to ensure clarity and comprehension among respondents [Andersen \(2022\)](#). It may also be biased depending on the process of the implementation. An Unbiased result by Delphi requires rigorous planning and execution [Nordensvard, Zhou, and Zhang \(2018\)](#). Researchers also use Semi-Structured Interviews (SSI) and Narrative Analysis to capture deeper insights that structured methods might overlook. SSI involves conducting in-depth, one-on-one interviews with key experts to capture their unique mental models and narratives about the future trajectory of converging fields. The limitation of this approach is its limited scalability and the difficulty in combining highly subjective, individual views into a collective, actionable consensus, though it offers richness of detail not found in large-scale group studies [Lewis, Ritchie, Ormston, Morrell, et al. \(2003\)](#). To mitigate these limitations, it is beneficial to combine them with other approaches, such as technology road mapping, which tackles the growing complexity of emerging technologies [Kanama, Kondo, and Yokoo \(2008\)](#). Technology road mapping, another qualitative method, helps in evaluating emerging technologies in complex settings by employing data analytics and foresight techniques to forecast future scenarios [Vaseashta \(2018\)](#). [Albright \(2003\)](#) used technology roadmapping to provide a structured framework for managing and plotting the future direction of converging technologies such as nanotechnology, biotechnology, information technology, and cognitive science (NBIC), specifically

by linking applications, challenges, and solutions to drive innovation. technology roadmapping, however, might not adequately handle the vast risks and investments needed in fields with high levels of complexity and technological uncertainty, necessitating public-private partnerships and stronger management tools [Kanama and Kondo \(2007\)](#). Although both the Delphi method and technology roadmapping are powerful qualitative foresight tools, they serve distinct yet highly complementary roles. The Delphi method excels at consensus-building, iteratively aggregating diverse expert judgments to reduce bias and achieve shared agreement on plausible future developments in highly uncertain domains [Aichholzer \(2009\)](#); [Nordensvard et al. \(2018\)](#). Technology roadmapping, in contrast, is fundamentally a strategic planning instrument that translates insights into a visual, time-based framework, linking current capabilities to long-term goals, identifying gaps, milestones, and required resources or partnerships [Albright \(2003\)](#); [Kanama et al. \(2008\)](#). Delphi is therefore typically strongest in the exploratory front-end (generating and harmonizing visions), while roadmapping is better in the prescriptive back-end (structuring implementation pathways). Their integration—using Delphi outputs as direct input for roadmap construction—is increasingly recommended and has been shown to produce more robust foresight outcomes in converging technology fields [Kanama et al. \(2008\)](#). Researchers are increasingly turning to quantitative approaches for the large-scale analysis of technological convergence because of the time-consuming nature, inherent subjectivity, and scaling challenges of purely qualitative methods.

2.3.2 Quantitative Approaches

Quantitative approaches to studying technological convergence offer scalable and objective methods to analyze large datasets, complementing the rich but subjective insights of qualitative methods [Geum, Kim, Lee, and Kim \(2012\)](#). Unlike qualitative approaches that capture human experiences and ethical considerations, quantitative methods focus on measurable indicators, such as patent filings or publication trends, to track the integration of fields. These methods are valued for their ability to handle large amounts of data and detect early signs of convergence between industries [Curran and Leker \(2011\)](#).

Patent Analysis

One well known quantitative method is patent analysis. By analyzing the volume, content, and citations of patents, researchers can map how technologies merge over time. Patent analysis relies on specific indicators to detect convergence early, such as the input-output coefficient, which measures the flow of technological knowledge between industries [Trappey, Trappey, Wu, and Lin \(2012\)](#); patent citation indicators, which track how often patents refer to each other to show cross-field influence [Karvonen and Kässi \(2013\)](#); and the patent coefficient, which quantifies the strength of technological overlap [Fai and von Tunzelmann \(2001\)](#). Despite its strengths, patent analysis has limitations. First, It may overlook emerging technologies not yet patented or fail to capture ethical and societal implications, which qualitative methods better address [Geum et al. \(2012\)](#). Moreover, while patent citations indicate knowledge flow, they do not always offer a direct or comprehensive measure of true intellectual influence [Alcacer and Gittelman \(2006\)](#). Furthermore, the presence of strategic citing and other noise in the patenting process can obscure the real scope of knowledge integration [Allison and Lemley \(1998\)](#).

Bibliometric Analysis and Hybridization

To address these limitations, researchers often combine patent data with other quantitative methods, such as bibliometric analysis. This approach studies scientific publication and citation patterns to map technological convergence [Cui, Tang, Zhang, and Dai \(2023\)](#). Since scientific publications are less subject to the strategic issues found in patent records, they provide a clearer and more detailed perspective on emerging trends and interactions, particularly during the early stages of convergence [Coccia and Wang \(2016\)](#). Increasingly, researchers are adopting hybrid approaches that explicitly integrate patent analysis with bibliometric analysis of scientific publications to have a more complete view of convergence. Patent data excel at revealing applied, industry-driven technological convergence, whereas publication data are good for detecting earlier, science-driven interdisciplinary knowledge flows that often precede patenting activity [Curran and Leker \(2011\)](#). This combination aids in forecasting the development of emerging technologies, allowing organizations to strategize effectively based on current research trends [Gerdsri and Daim \(2008\)](#). For example,

this methodology was used by [Taques \(2025\)](#) to map the scientific knowledge surrounding patent activity in the FinTech domain, leveraging multi-database publication analysis alongside patent data to track technological trajectories and intellectual property strategies in areas such as blockchain and AI-driven finance. Despite the valuable insights offered by integrating patent and bibliometric analysis, this methodology is not without challenges. Patent data remains underutilized in many academic fields, such as cleaner production, where the connection between patent activity and scientific output is still developing [Grunevald, Kipper, Moraes, and Haupt \(2023\)](#). Furthermore, research output using patent data is subject to geographical disparities, with some regions, like Brazil, lagging behind in contributions [da Cruz and Paixão \(2018\)](#). These challenges highlight the ongoing need for further methodological application and exploration across diverse fields and global regions.

2.3.3 Network-Based Indicators

Building upon established bibliometric approaches [Ávila Robinson and Miyazaki \(2013\)](#), researchers have increasingly adopted network-based indicators to trace the interdisciplinary integration of knowledge. These sophisticated metrics are derived from relational structures (e.g., co-authorship links, citation flows, and keyword associations) found in both publication and patent databases, enabling the mapping of knowledge convergence as a structural process. The primary indicators used to detect and track this convergence include:

- **Co-word frequency and Co-citation strength:** These metrics measure the proximity and frequency of knowledge exchange between two distinct disciplines or technological domains. A rising co-citation strength between two previously disparate knowledge bases is a powerful indicator of their structural integration.
- **Network Centrality Measures:** Metrics such as Betweenness Centrality identify specific institutions, researchers, or papers that act as critical bridges connecting otherwise disconnected intellectual clusters. These high-centrality nodes are often the most valuable convergence catalysts.
- **Network Density:** This indicator measures the completeness of linkages within a knowledge

cluster; a rising density between formerly separate technological fields signals the rapid consolidation and maturity of a new hybrid domain.

For example, [Al, Taşkın, and Düzyol \(2012\)](#) applied social network analysis (SNA) to 14,365 Turkish surgery publications, using co-authorship and keyword co-occurrence networks. Centrality measures (e.g., betweenness) revealed the USA as the dominant collaborator and countries like Lebanon as critical bridges, demonstrating how network-based indicators uncover structural patterns beyond simple counts. [Chen \(2011\)](#) analyzed over 600,000 nanotechnology papers from Web of Science, constructing co-citation networks and identifying clusters of foundational works. By tracking rising co-citation strength between biotechnology and materials science documents, they detected the emergence of bio-nanotechnology nearly a decade before its mainstream recognition. These network-based approaches allow researchers to move beyond simple publication counts to map the structural dynamics of knowledge convergence, providing a robust foundation for identifying emerging technologies at their earliest stages.

2.3.4 Hybrid and Emerging Methodologies

The persistent limitations of traditional qualitative and quantitative approaches have strongly motivated the rapid development of hybrid and emerging methodologies. Qualitative methods, while rich in contextual depth, remain vulnerable to expert bias, limited scalability, and high subjectivity in interpreting narratives or achieving consensus [Andersen \(2022\)](#); [Lewis et al. \(2003\)](#). Quantitative and bibliometric approaches, despite their objectivity and scalability, suffer from data noise (e.g., strategic patenting or citation inflation), time lags between research and application, incomplete capture of emerging fields not yet formalized in patents or publications, and an over-reliance on structural indicators that often fail to grasp deep semantic relationships or dynamic evolutionary patterns [Alcacer and Gittelman \(2006\)](#); [Curran and Leker \(2011\)](#); [Geum et al. \(2012\)](#). These shortcomings drive the need for more advanced integrative frameworks capable of delivering dynamic and predictive insights into technological convergence. Advanced hybrid methodologies address many of these gaps by systematically combining multiple data streams (patents, publications, grants, clinical trials, etc.) with machine learning techniques to enable dynamic convergence mapping [Lee, Park, and Kang \(2018\)](#). Emerging approaches frequently integrate network metrics—such

as co-occurrence, citation, or collaboration networks—with supervised and unsupervised machine learning algorithms (e.g., link prediction, graph neural networks, or clustering) to transform static snapshots into predictive models of future convergence trajectories [Affuddin and Seo \(2025\)](#); [Kim and Geum \(2024\)](#). Such methods not only detect existing convergence more reliably than single-source analyses but also forecast potential future integration points, offering a crucial advantage in fast-moving domains where early identification translates directly into strategic priority. Most recently, AI-enhanced bibliometrics and patent analysis employing large language models (LLMs) and advanced Natural Language Processing (NLP) have emerged as particularly powerful tools for overcoming the semantic limitations of earlier methods. Traditional keyword indicators often miss subtle or cross-domain conceptual convergence, whereas LLM-based semantic embeddings, transformer architectures, and heterogeneous graph learning can capture contextual similarity, latent topics, and multi-dimensional knowledge flows at scale [Affuddin and Seo \(2025\)](#); [Kim and Lee \(2024\)](#); [Lee et al. \(2018\)](#). These approaches allow researchers to move beyond counting co-occurrences toward understanding of how knowledge recombines. For example, early bio-digital convergence in neural interface technologies or AI–quantum–biology interfaces long before they appear in traditional metrics. By automating classification, summarizing massive corpora, and generating interpretable convergence intelligence, LLM-enhanced methods directly support the kind of real-time foresight required for effective governance and innovation strategy in rapidly converging scientific and technological ecosystems [Oecd \(2016\)](#). While these emerging AI-driven methodologies represent a major advance, they introduce new critical considerations; dependency on training data quality and coverage, risks of embedded biases in pretrained models, interpretability challenges in deep learning systems, and high computational demands that may limit accessibility [Mohammed and Kora \(2025\)](#) [Moradi, Yan, Colwell, Samwald, and Asgari \(2025\)](#). Nevertheless, their ability to mitigate subjectivity, reduce noise through contextual understanding [Seo and Affuddin \(2024\)](#), capture dynamic evolution [Lee, Hong, and Kim \(2021\)](#), and operate at unprecedented scale positions them as the most promising foundation for future research on technological and scientific convergence [Lee et al. \(2021\)](#).

2.4 Network and Semantic Analysis as the Primary Lens

The evolution from traditional bibliometric indicators to network-based approaches represents a shift in the study of technological and scientific convergence. While basic quantitative data, such as publication counts and citation frequencies derived from bibliometric sources, provide signals of growth and impact, these sources remain fundamentally limited in capturing the relational dynamics and conceptual evolution that drive interdisciplinary integration [Mugabushaka, Kyriakou, and Papazoglou \(2015\)](#). Therefore, this study adopts a robust, hybrid methodological pipeline combining dynamic network analysis with advanced semantic modeling. Network analysis offers a more nuanced perspective, transforming raw publication and patent data into structured maps of knowledge flow and collaboration [Lee, Kogler, and Lee \(2019\)](#). As demonstrated in previous sections, network-based indicators such as co-citation strength [Chen \(2011\)](#) and centrality in collaboration graphs [Al et al. \(2012\)](#) reveal not only that convergence is occurring, but how and through whom it unfolds [Bhatt, Hsu, Lai, and Drave \(2025\)](#). This network lens is particularly powerful for analyzing dynamic processes. This methodology moves from static snapshots to a cinematic view of scientific evolution by constructing cumulative citation networks over sequential time windows. This dynamic approach allows for the observation of key phenomena, such as birth and death of research communities, the fusion of previously separate intellectual clusters (identified via the Fast-Newman topology clustering), and the divergence of a field into specialized subfields.

However, a significant challenge in this domain has historically been moving beyond purely topological analysis (the structure of the network) to deep semantic interpretation (the conceptual meaning of the clusters) [Giordano, Chiarello, Melluso, Fantoni, and Bonaccorsi \(2021\)](#). Early studies often relied on manual inspection or simple keyword frequencies to label communities, a process that is difficult to scale and potentially subjective [Giordano et al. \(2021\)](#). To overcome this inherent limitation, this work integrates LLMs and advanced NLP with network analysis. By using BERT embeddings (Section 4.3) and GPT-4 for topic label generation (Section 4.4), this approach enables the reliable identification of subtle, cross-domain conceptual integration. This semantic understanding moves beyond structural coincidence to deliver genuine, scalable insights into the mechanisms of AI convergence. This thesis directly addresses this challenge by integrating LLM with dynamic

network analysis. We employ BERTopic, a topic modeling technique, to semantically ground the communities identified through citation network clustering. This hybrid methodology combining the structural clarity of the Fast-Newman algorithm with the semantic depth of transformer, based language models, provides a more nuanced and interpretable framework for mapping knowledge convergence. It allows us to not only detect when two fields merge but also to characterize the thematic content of the resulting new field. By applying this framework to the rich corpus of Canadian AI research, this thesis aims to provide a comprehensive, data-driven account of the patterns and drivers of scientific convergence, thereby offering a scalable, reproducible, and structurally informed model for anticipating the future of innovation.

2.4.1 Future Directions: Predictive Convergence Mapping and Policy

The methodological trajectory reviewed in this section indicates a shift from static, retrospective analysis toward dynamic and predictive convergence mapping. The core future direction for research lies in systematically leveraging the power of AI-enhanced methods to generate actionable foresight for innovation policy [Kolapo and Adeyemo \(2025\)](#). The immediate frontier involves moving beyond the use of network indicators (like co-citation and centrality) for just detection to utilizing them as features in predictive machine learning models [Wang and Lee \(2023\)](#). These models can forecast which currently separate scientific and technological clusters are most likely to merge in the coming years. This transition converts convergence analysis from a descriptive academic exercise into a strategic planning tool [Afifuddin and Seo \(2024\)](#). Future research must emphasize the semantic understanding offered by advanced LLMs. While topological network analysis can identify where the knowledge is mixing, semantic modeling reveals what the new, integrated knowledge domain is about [Sternfeld et al. \(2025\)](#). This depth is necessary for policy relevance, allowing governments and funding agencies (like those in the Pan-Canadian AI Strategy) to anticipate the necessary skill sets and regulatory adjustments for emerging fields [Attard-Frost, Brandusescu, and Lyons \(2024b\)](#).

A significant gap remains in linking convergence analysis directly to policy impact. Future work should integrate network and semantic-based findings with established policy evaluation metrics. For example, measuring how national funding (e.g., the CIFAR investment) accelerates the merger

of specific high-priority research clusters. This connection is crucial for validating national strategic investments. As AI-enhanced methods become standard, future research must also focus on developing methods for interpreting the results of deep learning models. Ensuring the findings remain transparent, explainable, and free from inherited biases is critical for regulatory acceptance and maintaining the academic integrity of the convergence maps [Monteiro and Reynoso-Meza \(2022\)](#). This represents the final convergence challenge which is fusing complex computational power with human trust and accountability.

Chapter 3

Data

This chapter provides a detailed description of the data retrieval process, including the selection of the primary source, the execution of the search query, and the filtering steps required to generate the final corpus of Canadian AI research publications used for dynamic network analysis.

3.1 Data Collection and Filtering

Data collection and preparation involved several steps. First, We utilized Elsevier’s Scopus database to extract AI-related scientific publications, published between 2000 and 2023. The query search included: (“artificial intelligence” OR “machine learning” OR “deep learning”) to extract AI-related publications where at least one of the mentioned phrases appeared in the title/abstract of the publication or in the keywords section. This search resulted in a total of 1,234,816 publications, with data extracted on November 1, 2024. To refine the dataset, we applied a country/territory filter in Scopus to include only publications affiliated with Canadian institutions, reducing the dataset to 43,903 publications. We further refined the dataset by filtering document types to include only “Journal Articles”, “Conference Papers”, and “Reviews”, which resulted in 41,619 publications. Additionally, we removed duplicate entries and any papers with null values for the title or year of publication. This final filtering process resulted in a target dataset of 41,556 publications, which we utilized for further analysis. We then retrieved the citation information for each publication directly from the Scopus database. Fig. 3.1 shows the distribution of papers in the target dataset.

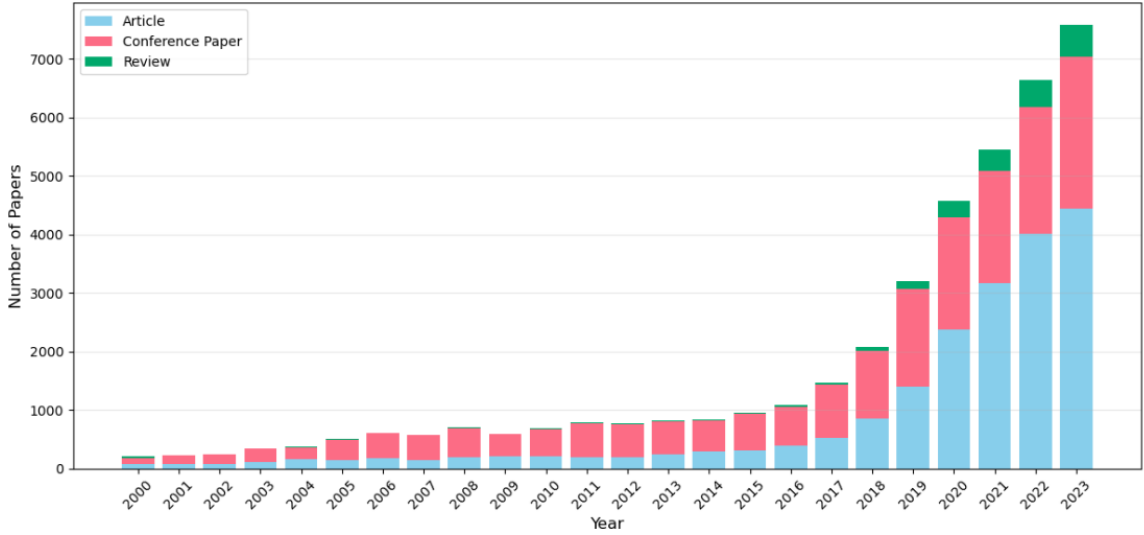


Figure 3.1: Annual distribution of publications by document type in the dataset ($n = 41,556$).

3.2 Data Preprocessing

To prepare the textual data for analysis, we applied preprocessing steps to the combined titles and abstracts of the publications. Initially, all text was converted to lowercase to ensure consistency. We then utilized the NLTK Python library [Bird, Klein, and Loper \(2009\)](#), a comprehensive toolkit for natural language processing that provides efficient algorithms for text manipulation, for tokenization, which involved splitting the text into individual words (tokens). To concentrate the analysis on meaningful lexical content, punctuation marks were removed. Next, we employed lemmatization with NLTK, leveraging its integration with the WordNet lexical database [Miller \(1995\)](#) to reduce words to their base or dictionary forms while preserving linguistic context. Finally, NLTK was used to remove non-informative words and common English stopwords via its pre-compiled corpus of high-frequency function words, streamlining the dataset for analysis.

Chapter 4

Methodology

This chapter provides a detailed description of the methodology and the analytical pipeline. In Fig. 4.1, the high-level conceptual flow of the analytical pipeline is presented. The experiments were conducted on an Acer laptop equipped with a 2.90 GHz CPU, 16 GB of RAM, and 500 GB of storage. All coding was executed using Python version 3.12.3.

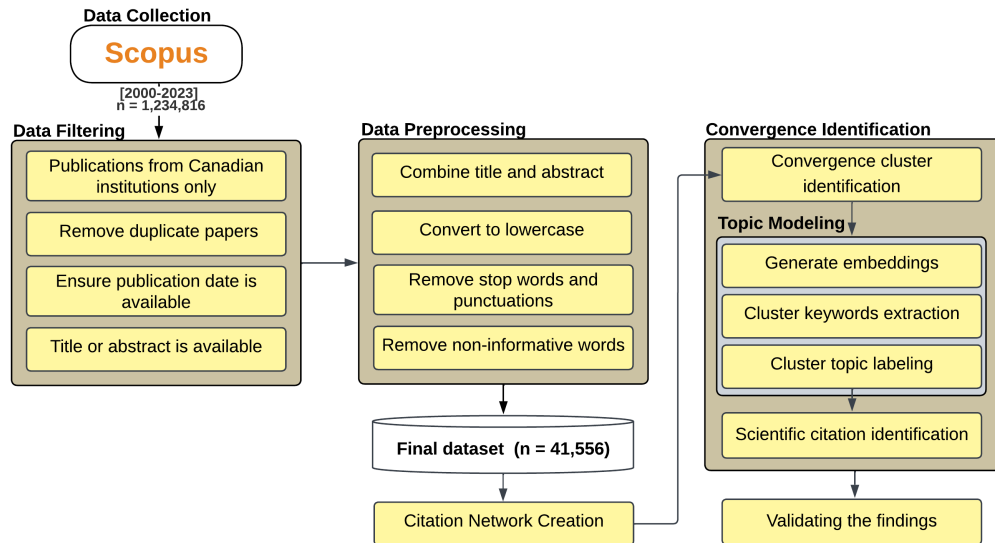


Figure 4.1: Overview of the high-level conceptual flow in the analytical pipeline.

4.1 Citation Network Creation

After collecting the publications and retrieving the citation data, we built separate cumulative networks for each year to trace the temporal evolution of knowledge convergence. This approach reflects how a scientific field accretes knowledge over time, new publications build upon the entire existing literature, not just the work from the previous year. Let $P = [P_1, P_2, P_3, \dots, P_n]$ denote the data set of papers over time, where P_n represents the set of papers from the start date, i.e., 2000, up to year n ($max_n = 2023$). Next, we applied the same process to the citation data set. After separating the data set for each cumulative year, we constructed a network where nodes represent publications characterized by their title, abstract, and publication date, and edges depict citation relationships between them. In the resulting paper citation networks, $N = [N_1, N_2, N_3, \dots, N_n]$ denote the networks, where N_i corresponds to the network constructed from the paper dataset P_i .

4.2 Newman Topology Clustering

Many real-world networks, such as citation networks, often exhibit distinct community structures. These structures can be identified using various methods, though not all are equally effective for every network type. The hierarchical clustering method (HCM) is a popular data mining technique that organizes data into a tree-like structure, offering a clear visual representation of data relationships through dendrograms [Kaur and Madaan \(2016\)](#). However, HCM requires predefined parameters, such as the number of clusters, which are often unknown in advance, and lacks a global optimization objective, leading to potential poor performance issues in datasets with complex relationships [Rahgoshay and Salavatipour \(2021\)](#). The self-organizing feature map (SOFM) is another clustering method that projects high-dimensional data into a lower-dimensional space while maintaining the topological properties. It is versatile for complex and non-linear data [J. Zhang, Li, and Li \(2010\)](#), but requires prior knowledge of the data structure [Kohonen \(1982\)](#). Meanwhile, K-means clustering [MacQueen \(1967\)](#) is another widely utilized algorithm, which is efficient, particularly with large datasets, as it converges quickly [Wang and Su \(2011\)](#). K-means also necessitates prior specification of the number of clusters, which can lead to suboptimal clustering results [Ahmed, Seraj, and Islam \(2020\)](#). Random selection of initial centroids can result in different clustering

outcomes, affecting consistency [Ahmed et al. \(2020\)](#). The Girvan-Newman (GN) algorithm [Girvan and Newman \(2002\)](#), designed for community detection in complex networks, utilizes edge betweenness to identify and separate communities. By iteratively removing edges with the highest betweenness, it constructs a dendrogram that reveals the hierarchical structure of communities within the network [Palacio-Niño and Berzal \(2024\)](#). In 2004, the Fast-Newman (FN) algorithm, also known as the greedy modularity optimization algorithm [Newman \(2004\)](#), was introduced to enhance the GN algorithm’s efficiency. It employs a greedy approach to merge communities in a way that maximizes modularity, enabling faster processing of large networks. The modularity function in the FN algorithm provides a global optimization objective, addressing the GN algorithm’s reliance on local edge-betweenness heuristics [Newman \(2004\)](#). Unlike other clustering algorithms, such as k-means and hierarchical clustering, which require the pre-specification of the number of clusters—a potential source of inaccuracies [Shi, Zhu, Li, Liu, and Cheng \(2021\)](#)—the FN algorithm identifies the most suitable number of clusters automatically by finding natural grouping patterns within the network. The optimization technique used by the FN algorithm is the maximization of the modularity function (Q), as defined in Equation (1):

$$Q = \sum_s (e_{st} - a_s^2)^2 = \text{Tr}(e) - \|e\|^2, \quad (1)$$

where e_{st} represents the density of interconnected nodes between clusters s and t , $a_s = \sum_t e_{st}$ is sum of connection densities, and $\text{Tr}(e)$ gives the sum of the connection density within each cluster, also known as the trace of the matrix e . $\|e\|^2$ denotes the sum of the density of connections within each cluster when all connections are randomly generated. A higher modularity value indicates a more effective network division, signifying better clustering results. Motivated by these properties, we used the FN clustering algorithm in this work. The FN algorithm allows for the detection of natural community structures within each yearly cumulative citation network, with the modularity score indicating the strength of these structures. The number of communities resulting from this method is shown in Table [A.1](#) in Appendix [A](#).

4.3 Topic Modeling

To uncover the thematic content of converging fields, we employed BERTopic [Grootendorst \(2022\)](#), a topic modelling technique that leverages Bidirectional Encoder Representations from Transformers (BERT) [Devlin, Chang, Lee, and Toutanova \(2018\)](#) embeddings. BERTopic was applied to the combined titles and abstracts of publications within each community identified by the FN clustering algorithm in the paper citation network. BERTopic uses BERT to generate contextual embeddings and extract interpretable topics [Grootendorst \(2022\)](#). After preprocessing, we generated publication embeddings using `all-MiniLM-L6-v2` Sentence-BERT model [Reimers and Gurevych \(2019\)](#) from the `sentence-transformers` library, sourced from the HuggingFace hub, which is specifically designed for generating high-quality sentence embeddings. For keyword extraction, we used the KeyBERTInspired representation model within BERTopic [Grootendorst \(2020\)](#). The KeyBERTInspired model is used to generate the top keywords for each topic as part of the topic modeling output. This is controlled by the `top_n_words=5` parameter, which asks BERTopic to return the five most relevant keywords per topic. These keywords were not extracted separately using the standalone KeyBERT library. We then applied a two-step unsupervised learning approach, Uniform Manifold Approximation and Projection (UMAP) [Healy and McInnes \(2024\)](#) for dimensionality reduction [McInnes, Healy, Saul, and Grossberger \(2018\)](#), followed by Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) [McInnes, Healy, Astels, et al. \(2017\)](#) for clustering. This approach allowed the number of generated topics to be determined naturally by the data structures. HDBSCAN identifies clusters by analyzing the density distribution of data points in the embedding space, with a minimum cluster size set to 15, justified later in Section 4.5. UMAP projected the high-dimensional embeddings into a lower-dimensional space, preserving both local and global data structures, with a neighbor count set to 30, justified in Section 4.5.

4.4 Topic Label Generation

To interpret and assign meaningful labels to each topic, we used the GPT-4 model [Achiam et al. \(2023\)](#) to generate concise topic labels from keywords in each community. This approach

was justified by GPT-4’s documented advancements in language understanding. With a model size exceeding one trillion parameters, GPT-4 demonstrates a superior capacity for nuanced language generation and contextual reasoning compared to previous models [Baktash and Dawodi \(2023\)](#); [Koubaa \(2023\)](#). This enables it to infer the underlying thematic connection between keywords and representative documents, producing a semantically meaningful label rather than a simple keyword list. This generative step is guided by a few-shot prompt that we designed. The prompt included three components:

- (1) A system prompt that defined the model’s role.
- (2) Few-Shot examples prompt for providing input-output pairs to demonstrate the desired format for topic labels.
- (3) The main prompt, which dynamically integrated the topic’s representative documents and keywords to serve as contextual cues for the model.

This approach combines computational precision with interpretive clarity, facilitating the identification of latent themes within the publication corpus.

4.5 Topic Quality Evaluation

To evaluate the quality of the topics and associated keywords generated by our designed model, we employed the Topic Coherence (C_V , Equation (2)) metric [Röder, Both, and Hinneburg \(2015\)](#), which quantifies the semantic consistency within each topic based on word co-occurrence patterns in the corpus. A higher C_V score indicates that a topic is more interpretable and cohesive, reflecting stronger semantic connections among its keywords. In Equation (2), t is a topic, w_i and w_j are keywords in topic t , N is the number of keywords in the topic, and $\text{PMI}(w_i, w_j)$ is the pointwise mutual information between words w_i and w_j (Equation (3)).

$$C_V(t) = \frac{1}{\binom{N}{2}} \sum_{i < j} \text{PMI}(w_i, w_j) \quad (2)$$

The PMI measures the association between two words based on their co-occurrence probability

relative to their individual probabilities, defined as:

$$\text{PMI}(w_i, w_j) = \log \frac{P(w_i, w_j)}{P(w_i)P(w_j)} \quad (3)$$

where $P(w_i, w_j)$ is the joint probability of words w_i and w_j co-occurring in the corpus, and $P(w_i)$ and $P(w_j)$ are the individual probabilities of words w_i and w_j appearing in the corpus.

We calculated the average coherence C_V with different UMAP hyperparameters ($n_{\text{neighbors}} \in \{5, 15, 30\}$) for all the communities in 2023 (detected by the FN algorithm), $n = 8, 101$, finding that the results were consistent with a clear improvement with larger neighborhood sizes. Increasing $n_{\text{neighbors}}$ from 5 to 30 raised the average coherence C_V from 0.7017 (± 0.0980) to 0.7463 (± 0.0888), while reducing variability across topics. For UMAP, we selected $n_{\text{neighbors}} = 30$ to prioritize the preservation of global data structures, as it yielded a higher average topic coherence. This choice was motivated by our dataset’s diverse thematic content, where capturing global relationships ensured more semantically cohesive topics. While further increases in $n_{\text{neighbors}}$ might offer marginal improvements in C_V , the selection of 30 was considered optimal since it represented a good trade-off between the maximization of the global data structure preservation—essential for the detection of broad themes of convergence—and computational resource/time complexity that increases disproportionately for higher values. For HDBSCAN, a minimum cluster size of 15 was chosen based on preliminary experiments to effectively filter out noise and ensure the formation of meaningful clusters. Smaller minimum cluster sizes can lead to a proliferation of micro-clusters, particularly in high-density regions, which may not reflect significant patterns in the data [Malzer and Baum \(2019\)](#). While smaller sizes might enhance the detection of finer structures, they also increase computational demands due to HDBSCAN’s hierarchical nature, requiring additional processing time to evaluate cluster stability and extract meaningful clusters [Neto, Sander, Campello, and Nascimento \(2019\)](#).

4.6 Convergence Cluster Identification and Pathway Analysis

After extracting keywords and identifying labels, we analyzed how clusters evolved over time by calculating their overlap across consecutive years. When a cluster in year t shares a substantial

number of papers with a cluster in year $t + 1$, it suggests that the topic either persists or evolves into the next period. Using this approach, we traced the transition patterns between clusters to map the evolution pathways of scientific convergence. Our method is inspired by the approach in [Spiliopoulou, Ntoutsis, Theodoridis, and Schult \(2006\)](#). The MONIC framework, introduced by [Spiliopoulou et al. \(2006\)](#), provides a comprehensive approach for modeling and tracking cluster transitions, particularly in accumulating data streams. We chose this method since it is inherently designed to handle the non-static, cumulative nature of citation data (where the underlying knowledge space changes yearly), ensuring that our measured overlap reflects genuine thematic evolution rather than simple structural shifts. This approach is crucial because it allows for the identification of changes even when the underlying feature space evolves, distinguishing it from methods that rely on fixed topological properties or metric spaces. The overlap between a cluster C_t at time t and a cluster C_{t+1} at time $t + 1$ is defined as:

$$\text{overlap}(C_t, C_{t+1}) = \frac{|C_t \cap C_{t+1}|}{|C_t|}, \quad (4)$$

where C_t is the set of nodes in the cluster at time t , $|C_t|$ is the number of nodes in that cluster, and $|C_t \cap C_{t+1}|$ is the number of nodes common to both clusters. Clusters whose overlap exceeds a certain threshold are considered to have a transition relationship. These linked clusters, labeled with their topics and time periods, collectively form the evolution pathways of scientific convergence.

Chapter 5

Results

In this section, we first discuss three distinct patterns of fusion that were discovered, and then we present our findings about the observed technological patterns.

5.1 Convergence Mechanism

5.1.1 Generative Convergence Pattern

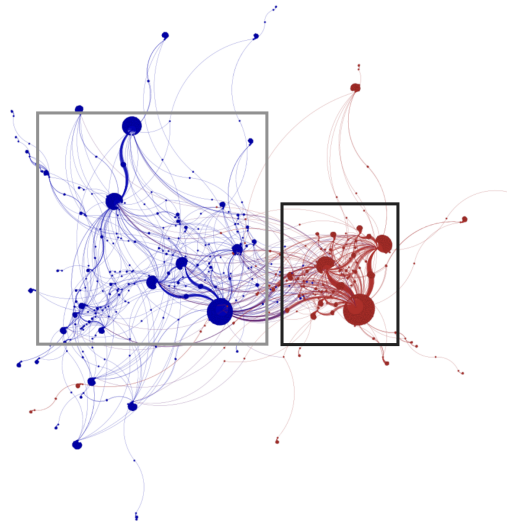
The first pattern, named “*Generative Convergence (GC)*”, occurs when two fields, A and B , interact to give rise to a new, distinct field ($A+B \rightarrow A+B+C$). This emerging discipline, C , is not just a blend of the preceding fields but rather a separate entity with its own unique goals, methods, and identity. Importantly, fields A and B continue to exist independently after the convergence. The field of computational biology represents a clear instance of Generative Convergence, resulting from the fusion of computer science and molecular biology [Ouzounis and Valencia \(2003\)](#). This new discipline focuses on the development of unique algorithms to interpret massive genomic datasets, possessing its own methodologies that are separate from the experimental work of biology and the general theoretical work of computer science. To classify a fusion as GC, we empirically calibrated and set a threshold whereby the new field C must comprise at least 40% of papers from both A and B , ensuring significant influence from each parent field. For cases where the percentages are below this threshold, the fusion is still occurring, but we do not designate it as a GC. For cases involving more than two parent fields, we accept contributions of at least 10% of papers from each parent.

Case Study

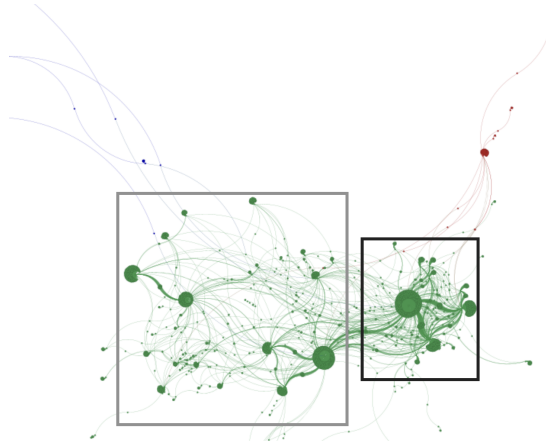
In 2009, for instance, community 341 within our network (focused on “Electrical System Diagnostics”, and “Mining Operations and Optimization”) and community 481 (“Missing Data Handling and Imputation”) interacted to form a new field in 2010 centered on “Predictive Analytics”, “Intelligent Missing Data Handling”, and “Tree-based Machine Learning Algorithms”. This new field, C , comprises a significant proportion of papers from both A and B , with 50% from A and 40% from B , demonstrating strong influences from both parent fields while maintaining a distinct identity separate from either A or B . This new community showcases a logical progression in their convergence, applying specific advanced machine learning algorithms, such as fuzzy decision trees [Chang and Pavlidis \(2007\)](#), to the specific challenges of electrical system diagnostics. Fig. 5.1a depicts the network in 2009, highlighting Community 481 in red and Community 341 in blue. In contrast, Fig. 5.1b illustrates the network in 2010, where Community 888, shown in green, emerges as the result of the convergence of Communities 481 and 341, while remaining connected to Community 481 (red) and Community 341 (blue).

5.1.2 Transformative Convergence Pattern

The second pattern, which we named “*Transformative Convergence (TC)*”, occurs when two fields, A and B , interact, resulting in a new field that retains the nominal identity (e.g., label or core disciplinary affiliation) of one of the parent fields (A) but undergoes a substantial transformation in its scope, methods, or focus. Meanwhile, B continues to exist independently. This transformation can be expressed as $A + B \rightarrow A' + B$. To classify a fusion as TC, we empirically calibrated and set a threshold where the transformed field (A') must incorporate at least 10% of its papers from field B , reflecting a significant influence, while at least 50% of A' retains the core identity or topics of A , ensuring the nominal continuity of A despite its transformation. The rise of computational social science provides an example of this pattern [Lazer et al. \(2009\)](#). Traditional sociological inquiry has been altered by the deep integration of methodologies from computer science, specifically through the analysis of large-scale digital trace data. While retaining the core disciplinary goals



(a) 2009



(b) 2010

Figure 5.1: Sample paper citation networks demonstrating the convergence of two fields and the emergence of a new field: Community 341 (blue) + Community 481 (red) $\rightarrow$ Community 888 (green).

of understanding human behavior, the transformed field (A') now relies heavily on tools like network analysis and machine learning, fundamentally altering its research scope and methods without dissolving the identity of the original field.

Case Study

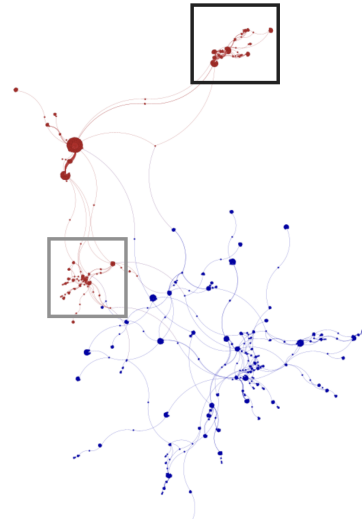
Fig. 5.2 depicts a sample from our networks in 2013 (Fig. 5.2a) and 2014 (Fig. 5.2b), representing the TC pattern. Fig. 5.2a shows the interaction between Community 41 (focused on “Advanced Knowledge Management”, A), colored in blue, with Community 839 (“Biomedical Data” and “Clinical Decision Support”, B), colored in red. The following year (Fig. 5.2b), Community 41 evolved into a new Community 41 (“Knowledge Management for Pervasive Healthcare”, A'), incorporating 11% of its papers from B while retaining 80% of its core “Advanced Knowledge Management” topics. This transformation reflects a significant shift in scope and methods while preserving A ’s nominal identity.

5.1.3 Divergence Pattern

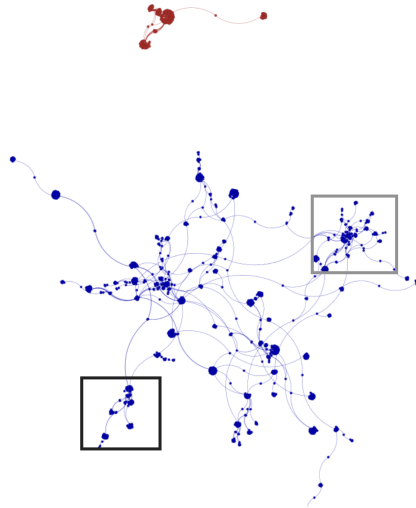
The third pattern, termed “*Divergence (D)*”, occurs when a broad field fragments into smaller, specialized subfields, each with its own unique focus and methodologies. For example, a large field, such as biology, may break down into subfields such as genomics, proteomics, and synthetic biology. Our study suggests that convergence and divergence are constantly intertwined, forming an adaptive cycle crucial for sustained innovation and growth. A discipline often begins by experiencing a period of methodological convergence, where researchers focus on refining a core set of foundational theories, algorithmic approaches, or experimental techniques. However, this intense focus simultaneously creates a condition of intellectual inertia, narrowing the scope of solvable problems and building pressure for change. Breakthroughs, then provide a necessary methodological divergence, wherein the field breaks with established paradigms to embrace radically different methodologies. This expansion, in most cases, is managed by the rapid re-convergence around the new, high-impact methodology, so that the field sustains its coherence by applying a single, dominant solution toolkit to an increasingly broad and diverse set of problems.

Case Study

In Fig 5.3a, we have illustrated an example of a community that underwent all three patterns discussed. In 2005, Community 5, colored in red, centered on “Medical Imaging” and “Neuroscience”



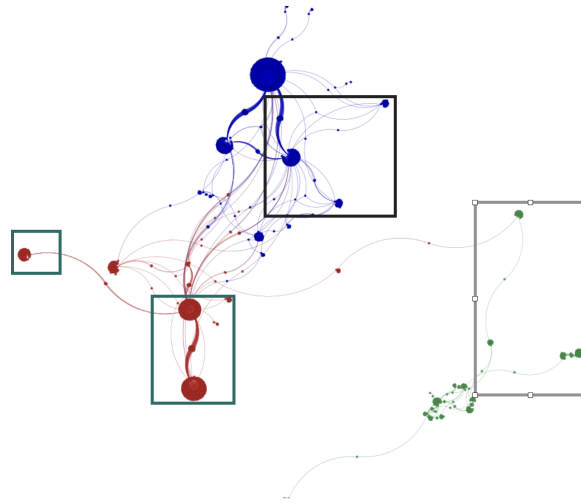
(a) 2013



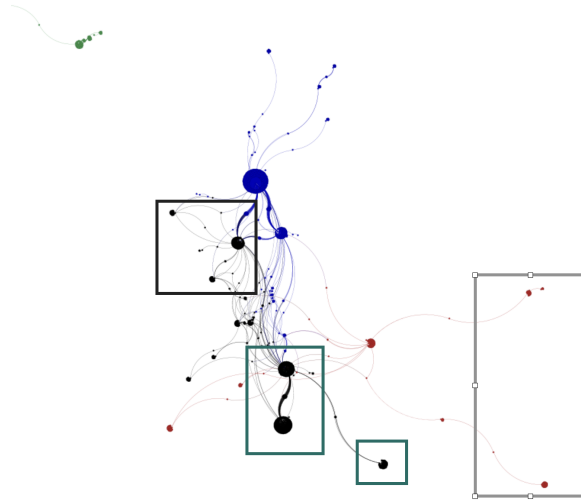
(b) 2014

Figure 5.2: Sample paper citation networks demonstrating the transformative convergence pattern: Community 41 (blue) + Community 839 (red) $\rightarrow$ New Community 41 + Community 839.

diverged. One segment underwent a TC with Community 235 in green. This fusion resulted in an evolved Community 5 in 2006, shown in red in Fig 5.3b. Meanwhile, another part of Community 5 had a GC with Community 213, colored in blue, which focused on “Radiomics Imaging”. This second merger created a new, independent community, colored in black, in 2006. The new community is focused on the analysis of specialized medical image data for clinical insights.



(a) 2005



(b) 2006

Figure 5.3: Sample paper citation networks demonstrating the divergence pattern: Community 5 (red) diverged, followed by transformative convergence with Community 235 (green) and generative convergence with Community 213 (blue), resulting in an evolved Community 5 (red) and a new specialized Community 316 (black) in 2006.

5.2 Pivotal Community Dynamics and Pathway Insights

Our analysis of community dynamics over cumulative years revealed that certain communities have played a crucial role in influencing patterns of technological convergence and divergence. In this section, we present and discuss four key communities and their impact on the broader landscape.

5.2.1 Game Theory

Among key communities, Community 15, labelled “Game Theory”, emerged as a significant hub due to its frequent interactions with other communities through both convergence and divergence processes. The complete list of topics and their associated top keywords for Community 15 and all interacting communities across the study period is provided in Appendix B.1, Table B.1. In its initial phase, “Game Theory” merged with fields such as “Automated and Temporal” (Community 170), “StarCraft Strategy”, and “Deep Reinforcement Learning in Real-Time Strategy Games” (Community 340) which leads to evolvement of “Game Theory”. In 2005, Community 15 merged with Community 93, “Lifted Probabilistic Relational Inference”, “Markov Decision Processes”, and “Fuzzy Logic Planning”, and Community 592, “Multi-Agent Path Planning”, and “Satisfiability-Based Path Finding”, leading to the development of “Warehouse Path Planning”, and “Multi-Agent Pickup and Delivery” (Community 126) in 2006. This new field recognized warehouses as multi-agent systems, leveraging game theory to model interactions among elements such as human workers, robots, and automated vehicles to optimize resource and task allocation. The convergence further evolved into a TC pattern where Community 15 expanded into “Agent-Based Game Learning and Path Planning”, “Real-Time Heuristic Search”, “Preference-Based Planning and Goal Setting”, and “Markov Probabilistic Logic Inference”. This transformation highlighted how practical demands in warehouse optimization spurred theoretical advancements in game theory. Strategy”, and “Deep Reinforcement Learning in Real-Time Strategy Games” (Community 340) which leads to evolvement of “Game Theory”. In 2007, Community 15 diverged into distinct research path-

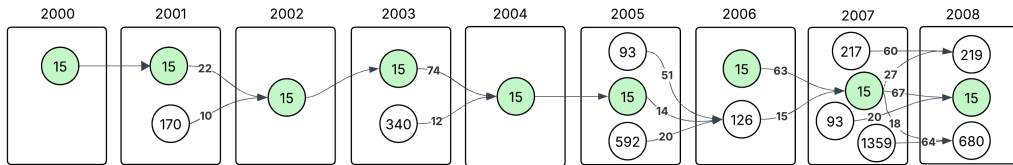


Figure 5.4: Trajectory of Community 15 from 2000 to 2008.

ways. A portion of it merged with fields focused on advanced reinforcement learning in multi-agent robotics (Community 217), resulting in advancements in “RoboCup Soccer Simulation” and “Real-Time Strategy Games” (Community 219). Concurrently, another component of Community 15

merged with areas such as “Automated Negotiation” and “Preference Representation” (Community 93), forming a new Community 15 centred on “Intelligent Agent Design and Interaction” and “Decision-Making under Uncertainty in Complex Systems”. This emerging field was crucial for addressing autonomous agents’ decision-making processes in complex scenarios, emphasizing ethical behavior in AI systems. Another convergence saw “Bayesian Optimization” merge with “Active Learning in Robotics” (Community 1359), leading to progress in areas such as “Bipedal Robot Gait Learning”, “Billiards and Pool Game Strategy”, and “Multi-Agent Learning and Equilibrium” (Community 680), underscoring the role of probabilistic reasoning in efficient robotic learning. Fig. 5.4 shows divergence and re-specialization pathways of Community 15 between 2000 and 2008. As the early-2010s approached, Community 15 continued to evolve. It converged with Community 16, specializing in “Reinforcement Learning with Policy and Stat”, “Altruistic Hedonic Games”, and “Spoken Dialogue and User Intention”, resulting in a focus on “Monte Carlo Tree Search for Game”, “Multiwinner Voting Manipulation and Rules”, and “Computer Poker Strategy and Competition”. This transformative convergence signified a shift from learning robotic behaviours in specific game settings to addressing more generalized, real-world multi-agent system control and intelligence. Eventually, Community 15 merged with Community 288 to form Community 88, a synthesis of practical, learning-based multi-agent systems with symbolic and logical foundations of intelligence. The resulting community bridged these learning and reasoning, dedicated to building agents capable of experiential learning rational interaction, reflected in its focus on “Belief Revision and Change Calculus”, “Multi-Winner Voting Rules and Elections”, and ‘Multi-Agent Epistemic Planning with BDI’. Fig. 5.5 shows the trajectory of Community 15 from 2008 to 2016.

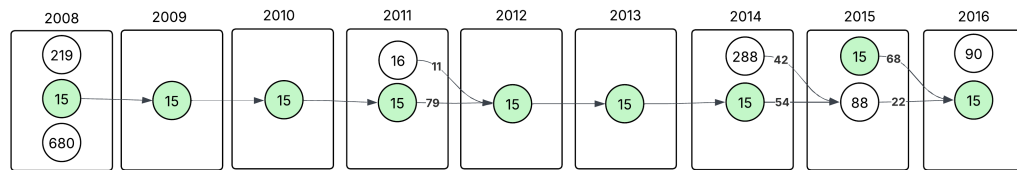


Figure 5.5: Trajectory of Community 15 from 2008 to 2016.

In 2016, as shown in Fig. 5.6, Community 15 had a TC with Community 90 centered on “Assistive Technology”, “Alzheimer’s and Dementia”, and “Ambient Assisted Living”. The result of this TC was an evolved Community 15 in 2017, centered on “Dementia Activity Monitoring with

Home Technology”, “Deep Neural Networks with Natural Gradient”, “Nondeterministic Planning Problems”, and “Imperfect Extensive-Form Game Equilibrium” containing two distinct research paths: healthcare applications and multi-agent systems. This TC was followed by a divergence in 2017. One segment of Community 15 merged with Community 16, “Fall Detection in Healthcare”, “Parkinson’s Disease Diagnosis”, “Activity Recognition”, and “Game-Theoretic Healthcare Monitoring”, resulting in an evolved Community 15 in 2018 which represents more of Community 16 labels and another part of Community 15 created Community 14 in 2018 with labels such as “Numeric and Classical Planning”, “Equilibrium in Imperfect Extensive-Form Games”, and “Multi-Winner Voting and Election Rules”.

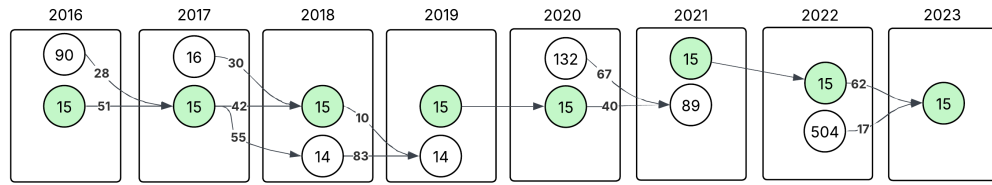


Figure 5.6: Trajectory of Community 15 from 2016 to 2023.

In 2018 and 2019, Communities 14 and 15 underwent a TC, mutually influencing each other during this period. By 2020, Community 15 merged with Community 132, which was centred on utilizing DL for diagnostic imaging and decision support. This merger led to the formation of Community 89 in 2021, characterized by labels such as “Prostate Cancer Biopsy and Gleason Grading”, “Skin Cancer and Melanoma Detection”, and “Autism Spectrum Disorder Diagnosis”. In 2022, Community 15 experienced another TC with Community 504, which focused on “Biomedical Signal Processing”, and “Causal Modelling”. As a result, the evolved Community 15 in 2023 concentrated on “Epileptic Seizure Detection and Epilepsy Analysis”, “Sleep Stage Classification”, and “EEG-Based Emotion Recognition”. Fig. 5.6 shows the trajectory of Community 15 from 2016 to 2023. Community 15’s journey from abstract game theory to applied medical diagnostics illustrates a case of methodological transference, where its core expertise in modeling strategic interaction and decision-making under uncertainty was redeployed to solve complex problems in healthcare.

Community 15: Network Visualization and Thematic Evaluation

Temporal analysis of Community 15’s network, illustrated in Fig. 5.7, shows a significant change in its methodological core, as well as in application focus, between 2017 and 2023. The complete node-label mapping for this network is provided for reference in the Appendix C, Table C.1.

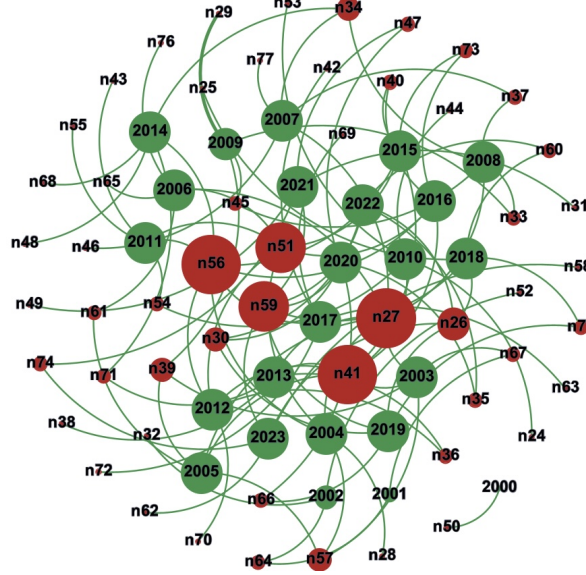


Figure 5.7: Temporal Network of Key Research Themes in Community 15: Labels in red and Years in green (2000–2023)

It is evident that this recent era constitutes the most important and central hub of the network, with dense connections to the most advanced and diverse keyword nodes, pointing to the community’s entry into the modern use of DL. The earlier research phase was defined by the principles of classical AI, focusing on search optimization, logic-based problems, and formal structures. The focus was explicitly on heuristic search, planning, and game AI. This focus is evident in research topics such as n41 (“Heuristic Search Algorithms”), n37 (“Real-Time Heuristic Search”), and n32 (“Heuristic Search Planning for Sokoban”). The main application was in solving formal, structured problems, specifically finding an optimal sequence of actions through planning and defeating an opponent in a constrained, logical environment through game AI, with notable examples being n27 (“Texas Hold’em Poker”), and n39 (“Chinese Chess Endgame Analysis”). The methodological shift began around 2013 and accelerated after the 2016, where data-driven techniques became

more dominant. The core emphasis shifted toward DL and DRL. This shift is represented by topics such as n56 (“Deep Multi-Agent Reinforcement Learning”) and n68 (“Deep Q-Learning and Q-Networks”). Additionally, the integration of “Monte Carlo Tree Search” (n51) has been crucial, as it’s a key component in recent successful DRL systems. The post-2016 period saw an expansion of application focus into critical, high-impact areas, such as healthcare and human-robot interaction. The tight clustering of these application nodes with the central DRL/DL hub shows the direct deployment of the community’s most advanced AI techniques toward practical, clinical problems. Healthcare/diagnostics included n59 (“Deep Learning for Human Activity Recognition”), n26 (“Fall Detection in Healthcare”), n58 (“Parkinson’s Disease-PD Assessment”), n75 (“Alzheimer’s and Dementia in People”), and n72 (“Dementia Activity Monitoring”). In parallel, the community’s expertise was combined with its new sensing and DL capabilities in robotics/assistive technology, by the appearance of topics such as n66 (“Robot-Mediated Rehabilitation”) and n35 (“Intelligent Assistive”).

5.2.2 Medical Imaging

Community 5, originally centred on “Medical Imaging”, emerged as a significant hub through various convergences and divergences in the early 2000s. The complete list of topics and their associated top keywords for Community 5 and all interacting communities across the study period is provided in Appendix B.2, Table B.2. Initially merging with Community 118, “Software Quality Classification”, it evolved into Community 115, labelled “fMRI-Based Functional and Spatial Activation Analysis”, and “Software Defect Prediction and Reliability”. A subsequent transformative convergence with Community 130, focused on “Case-Based Reasoning” expanded its scope to include “Bayesian Network Classifiers”, “Fuzzy Medical Information Classification”, and “Uncertainty Quantification in Medical Imaging”. In 2004, Community 5, underwent a divergence, leading to a TC with Community 625, emphasizing “Brain Functional Analysis”, “Feature Selection for Classification and Detection”, and “Radiomics for Liver Cancer Cell”, resulting in a more interdisciplinary focus that retained its core identity in “Quantitative Structure-Activity Relationship Modeling” and “Functional Brain Connectivity in Aging and Disorders”. Concurrently, another

segment of Community 5 collaborated with Community 341, “Fuzzy Neural Networks with Polynomial Features” and “ECG-Based Arrhythmia Classification and Disease Detection”, producing Community 235, which emphasized “Partial Discharge Pattern Recognition”, “Fuzzy Programming for Assignment Problems”, and “Pattern Classification”. By 2005, Community 5 further diverged, integrating with Community 235 to explore “Bayesian Network Classifiers”, “Fuzzy Medical Information Classification”, and “Fuzzy Programming for Assignment Problems”. It also converged with another community (Community 213) specializing in “Machine Learning for Disease Detection in Patients”, “Chest X-Ray Lung Image Analysis”, and “Protein-Protein Interaction Sequence Analysis”, forming Community 316. This progression highlights Community 5’s transition from a general medical imaging focus to advanced analytical methodologies for intelligent data interpretation, particularly using probabilistic reasoning and fuzzy logic, while Community 316 dedicated itself to the rigorous analysis of specialized medical image data for clinical insights. Fig. 5.8 illustrates the evolution of Community 5 between 2000 and 2008. In 2007, Community 5 merged

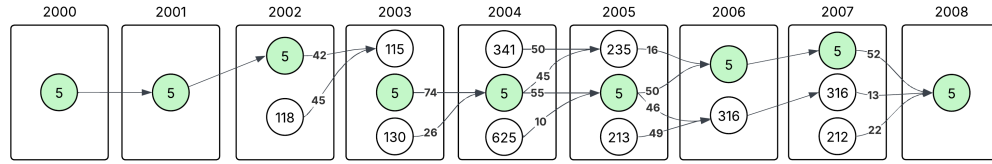


Figure 5.8: Trajectory of Community 5 from 2000 to 2008.

with Community 316 and received significant contributions from Community 212, which specialized in areas such as “Spam Email Filtering and Detection”, “Imbalanced Data Classification”, and “Gene Association Networks and Prediction”. By 2008, this convergence transformed Community 5 into a diverse hub labelled “Protein-Drug Interaction and Association Prediction” and “Alzheimer’s Disease Brain MRI Analysis”. This transformation marked a departure from a focus on specific methodologies to becoming a general-purpose centre for applied artificial intelligence and data science, addressing a wide array of complex problems. However, in 2009, Community 5 further merged with Community 198, known for predictive and diagnostic tasks across engineering and health domains, resulting in Community 80 in 2010. This new entity consolidated tasks such as “Software Defect Prediction” and “Protein Interaction Site Prediction”, signifying a shift to specialized predictive applications. Consequently, we re-examined the labels of Community 5 in

2010 and observed that it reverted to its 2005 focus on “Feature-Based Classification and Diagnosis Optimization” and “Intelligent Agent Decision Support” as Community 80 provided a dedicated space for its broader interests, allowing Community 5 to re-specialize on core AI/ML algorithms. In 2010, Community 5, having refocused on its core methodological strengths, merged with Community 608, dedicated to various clinical applications, including “Clinical Decision Support Systems” and “Gene Data Mining and Analysis”. This TC resulted in Community 5’s evolution by 2011 into an entity labelled “Clinical Decision Support” and “Neural Network Astrocytoma Brain Diagnosis”, demonstrating the application of its refined methodologies to real-world clinical challenges. Fig. 5.9 depicts the development of Community 5 between 2008 and 2018. In 2013, Community 5 underwent a complete realignment, merging with Community 58, which focused on “Heart Disease and Cancer Prediction” and “Sequential Pattern Mining”, resulting in a new identity characterized by “Sequential Pattern Mining” and “Privacy-Preserving Sensitive Data Hiding”. Meanwhile, another

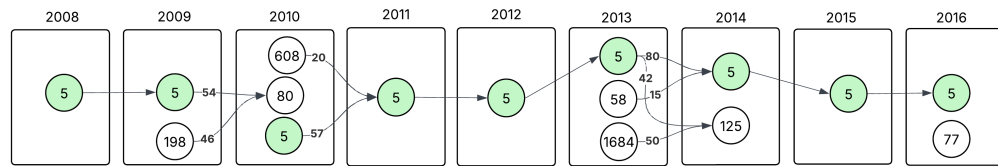


Figure 5.9: Trajectory of Community 5 from 2008 to 2016.

segment of Community 5 merged with Community 1684 focused on “Respiratory Sound Classification” and “Lung Sound Classification”, forming Community 125 in 2014. This new community dedicated itself to medical diagnosis using advanced signal and image analysis, highlighting a trend of Community 5’s adaptability and focus on integrating its computational methodologies into specific diagnostic and decision-making contexts. Fig. 5.9 illustrates the development of Community 5 from 2008 to 2016. In 2016, Community 5 merged with Community 77, a community focused on applying “Pattern Mining” for different areas, including healthcare and security (see Fig. 5.10). This TC resulted in Community 5’s evolution by 2017 with labels such as “Association Rule Mining”, and “Machine Learning for Heart Disease”. In 2017, Community 5 merged with Community 75, a group with interests in “Physiological Signal-Based Emotion Recognition”, “Cancer Detection”, “Software Reliability”, and “Element Mapping”, which led to the creation of Community

26 in 2018, centred on “Physiological Signal-Based Emotion Recognition”, and “Wireless Sensor Network Detection”. In 2018, Community 5 had a TC with Community 285, a hub for “PET-CT Tumor Segmentation”, “Deep Neural Networks”, “Cervical Cancer Diagnosis”, and “Gene Annotation and Protein Expression Splicing”. The resulting Community 5 in 2019 reflected a broader methodological focus, centred on “Anomaly Detection in Streaming Data”, “Association Rule Mining Classification”, and “Multilabel Classification and Learning”. Community 5 then shifted its application domain in 2019 by converging with 1852 centred on “Misinformation and Fake News Detection”. This union resulted in Community 57 in 2020, a hub focused on large-scale public data analysis, with labels such as “Mental Health and Anxiety During COVID-19”, “Twitter Sentiment and Topic Analysis”, “Chest X-Ray Image Analysis”, and “Drug Repurposing and Repositioning”. In 2020, Community 5 was involved in a double convergence. It merged with Community 1985, which was about “Localized Prostate Cancer and Biochemical Recurrence”, “Glaucoma Detection in Fundus Images”, “Molecular Breast Cancer Pathology”, and “Tumor-Infiltrating Lymphocytes in Breast Cancer” and Community 520, which was about “GNNs”, “Collaborative Filtering Recommendation”, and “EEG-Based Brain Emotion Recognition”. The resulting Community 5 in 2021 was focused on “GNNs for Multi-Omics Cancer Data Analysis” and “Collaborative Filtering for Biomarker Discovery”. In 2021, Community 5 diverged and converged. A segment detached to create Community 2889 in 2022, specializing in TDA application for Biomolecular and Physical Systems. The remaining part of Community 5 underwent a TC with Community 5148 (focused on “Wind Power Energy Storage”) and Community 3474 (“Hydrogen Storage in Alloys via Electrolysis”, “Smart Energy Analysis for Hydrogen Production”, and “Hydrogen Evolution Reaction”). The new Community 5 in 2022 was consequently highly concentrated on sustainable energy technologies, with an emphasis on the chemical and material science behind green hydrogen production. Lastly, in 2022, Community 5 once again diverged and converged. A part of it underwent a TC with Community 3713 (focused on “Vaccine Development”, and “Helminth Image Detection”) and Community 2111 (“Flow Cytometry Cell Data Analysis”, and “Leukemia Blood Image Classification”). The resulting Community 5 in 2023 was focused on “Deep Learning for Malaria and Parasite Diagnostics”, “Blood Cell Image Segmentation”, and “Fuzzy Medical Information Diagnosis”. Another part of this community merged with Community 291, focused on Hybrid Computational

Modeling applied across various fields of engineering and data mining with labels such as “Crop Nitrogen and Yield Fertilizer Optimization”, “Municipal Solid Waste Management”, and “Biochar Adsorption and Soil Remediation”. Together, they created Community 3454 in 2023, which was concentrated on “Wind Power Energy Storage”, “Proton Exchange Membrane Water Electrolysis”, and “Green Hydrogen Production”. Fig. 5.10 shows the trajectory of Community 5 from 2016 to 2023. The trajectory of Community 5 reveals that its identity was not confined to its initial applica-

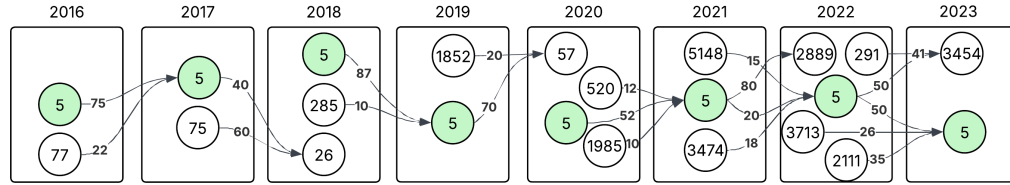


Figure 5.10: Trajectory of Community 5 from 2016 to 2023.

tion in “Medical Imaging”. Instead, the core expertise of the community lay in pattern recognition and predictive modeling.

Community 5: Network Visualization and Thematic Evaluation

Temporal analysis of Community 5’s network, as shown in Fig. 5.11, indicates that the community’s core foundational work is more distributed across the early-to-mid 2010s, and its methodologies have been consistently applied and refined rather than undergoing a sudden paradigm shift. The keyword labels reveal that Community 5’s long-term focus is in data mining, classification, diagnosis, and fuzzy logic applied across medical/healthcare and advanced computing domains. The complete node-label mapping for this network is provided for reference in the Appendix C, Table C.2.

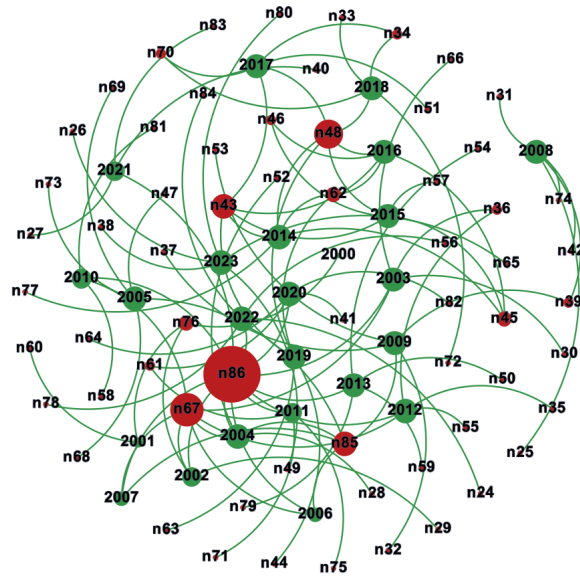


Figure 5.11: Temporal Network of Key Research Themes in Community 5: Labels in red and Years in green (2000–2023)

The early and mid-years are defined by a strong methodological convergence around algorithmic classification and data mining. Key nodes like n62 (“Association Rule Mining Classification”), n70 (“Association Rule Mining”), n45 (“Associative Classification”), and techniques for managing data heterogeneity, such as n37 (“Imbalanced Class Data Handling”) and n58 (“Feature-Based Classification”), constitute the essential toolkit developed during this period. A highly central sub-cluster is the consistent reliance on “Fuzzy Logic” for handling uncertainty and imprecision in data, especially in n86 (“Fuzzy Medical Information Classification”), n80 (“Fuzzy Medical Information Diagnosis”), and applied models like n59 (“Fuzzy Data-Driven Diagnosis Decision Support”). The post-2017 period is marked by strategic TC, where the foundational methodologies are expanded to integrate contemporary techniques and applied to novel, complex application domains. The community shows an adoption of GNNs. The appearance of n40 (“GNNs for Multi-Omics Cancer Data Analysis”) and n68 (“Graph Neural Networks and Kernel Classification”) in the 2017–2021 cluster shows a successful effort to apply advanced network-based methods to highly complex biological data. Importantly, thematic diversification is shown by the community’s unexpected introduction of applications in renewable energy. Nodes like n56 (“Green Hydrogen Production”), n24 (“Overall Water Splitting”), and n84 (“Wind Power Energy Storage”) are representative of a moving into

completely new physical sciences. The developments show the generalizability of the core competencies of data analysis and optimization that define the community. The 2019–2023 period acting as the modern integration hub illustrates the effort of the community to apply these latest techniques to both specialized clinical problems and novel energy domains.

5.2.3 Data Analytics

Community 41 began its journey in 2002 as a “Data Analytics” hub, but by the early 2000s, it had started converging with healthcare communities (namely Community 590), transforming into a “Medical Decision Support” Community. The complete list of topics and their associated top keywords for Community 41 and all interacting communities across the study period is provided in Appendix B.3, Table B.3. The convergence with Community 84, which specialized in “Automated Multi-Issue Negotiation Agents” and “Market-Based Negotiation Processes”, resulted in an evolved Community 41, now encompassing “Holonic Multi-Agent Negotiation in Manufacturing” alongside its medical decision support roots. This shift signaled an expansion of Community 41’s scope, integrating MAS capabilities to tackle complex healthcare challenges, including streamlining operations and logistics with advanced AI tools. In 2004, Community 41 experienced significant divergence, with its multi-agent negotiation expertise merging with Community 22, leading to a focus on “Shop Scheduling Problems” and “Holonic Manufacturing Control Architectures”, while its core medical decision support methodologies converged with Community 2 (“Natural Gas Pipeline Optimization” and “AI-Driven Remediation Management”), resulting in a broadened focus on environmental science, healthcare, and decision science. Then, Community 41 refocused through a merger with Community 277, specializing in “Healthcare Knowledge and Technology” and “Medical Case-Based Reasoning”, leading to a more emphasis on healthcare and protein imaging. Fig. 5.12 shows the evolution of Community 41 between 2000 and 2008. In 2010, as shown

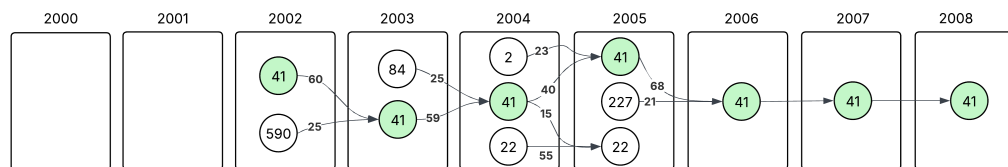


Figure 5.12: Trajectory of Community 41 from 2000 to 2008.

in Fig. 5.13, Community 41 underwent a complete divergence, splitting into three distinct parts. One segment converged with Community 2, resulting in an evolved Community 41 in 2011, which focused on advanced knowledge management and decision support across clinical and industrial applications. Another segment merged with Community 470, forming an evolved Community 470 in 2011, a hub for biomedical knowledge engineering and semantic data integration. The final segment of Community 41 formed its own independent community, 267, which centred on “Handheld Computer Use in Intensive Care”, “Healthcare Knowledge and Technology Translation”, and “Personal Digital Assistant Applications”, marking the end of Community 41’s distinct identity. Until the mid-2010s (see Fig. 5.13), Community 41 continues evolving and converging with Communities centred on “Smart Home and Assisted Living” (Community 140), “Fuzzy Decision Support for Diagnosis” (Community 125), and “Clinical Guidelines and Patient Decision Support” (Community 839). In 2015, Community 41, which focused on the application of data mining techniques to develop DSS in the domains of clinical medicine, underwent a complete divergence, splitting into four distinct research segments. One segment underwent a TC with Community 581 (“Texture-Based Image Classification”, and “Fabric Defect Detection”). The resulting evolved Community 41 in 2016 retained its applied focus on “Medical Decision Support”, but enhanced its methodological depth with “Texture-Based Image Classification” from Community 581. Another segment merged with Community 108, a hub for “Cross-Project Software Defect Prediction”, “Software Effort Estimation”, and “Bug Triage and Developer Assignment”. This union created Community 40 in 2016, which focuses on using predictive and analytical models to improve the quality, maintainability, and reliability of software systems. A third segment merged with Community 819, a research hub centred on “OWL Query Rewriting and Answering”, “Knowledge Graph Artifacts”, and “Linked Open Data”. This merger created Community 290 in 2016, which focused on “OWL Query Rewriting and Answering”, “Chemical and Drug-Drug Interaction Discovery”, and “SPARQL Query Benchmarking on RDF”. The final segment detached and created an independent community, Community 262, which focused on the human and organizational aspects of medical care, including “Reflective Learning and Practice Change”, “Handheld Mobile Computers in Healthcare”, and “Healthcare Knowledge Translation and Technology”. Community 41 continued its evolution in the following years, merging with Community 569 focusing on “Chemical Drug-Drug Discovery”, “Biomedical

Semantic Web”, and “SPARQL Querying on RDF”. In 2020, Community 41 diverged. One segment

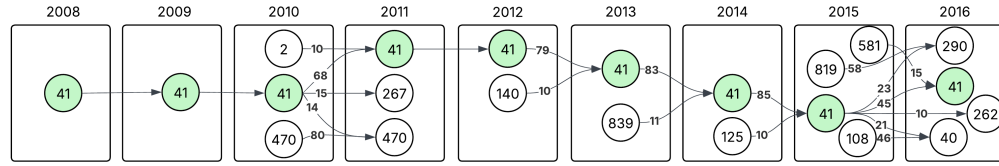


Figure 5.13: Trajectory of Community 41 from 2008 to 2016.

had a TC with Community 2, which was initially focused on “Knowledge-Based and DSS”, “Environmental and Climate Modeling”, and “Ant Colony Optimization (ACO)”. The resulting Community 2 in 2021 reflected a new focus on decision science, system management, and applied engineering in the environment. Concurrently, another segment of Community 41 merged with Community 871, a hub for “Prostate Cancer Biopsy and Prostatectomy”, “Microplastics Pollution Identification”, and “SERS Plasmonic Biosensors with Machine Learning”. This fusion resulted in Community 424 in 2021, which centred on analytical chemistry, biomedical computing, and control systems. This re-organization left the remaining Community 41 in 2021 with residual applied health labels such as “AI Cancer Chatbots”, “Smart Home Ambient Activity”, and “Depression and Depressive Disorder ” in 2021. Fig. 5.14 shows the trajectory of Community 41 from 2016 to 2023.

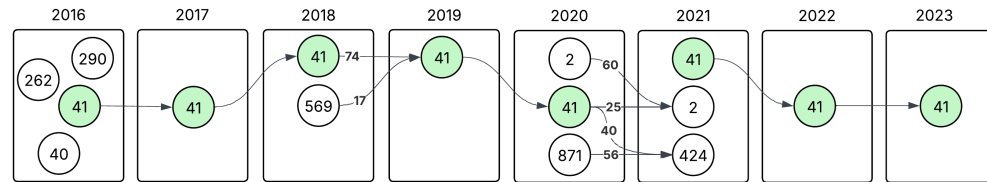


Figure 5.14: Trajectory of Community 41 from 2016 to 2023.

Community 41: Network Visualization and Thematic Evaluation

Temporal analysis of Community 41’s network (see Fig. 5.15), shows a focused, interlinked, and cohesive intellectual core that has remained dominant throughout the entire period. The complete node-label mapping for this network is provided for reference in the Appendix C, Table C.3.

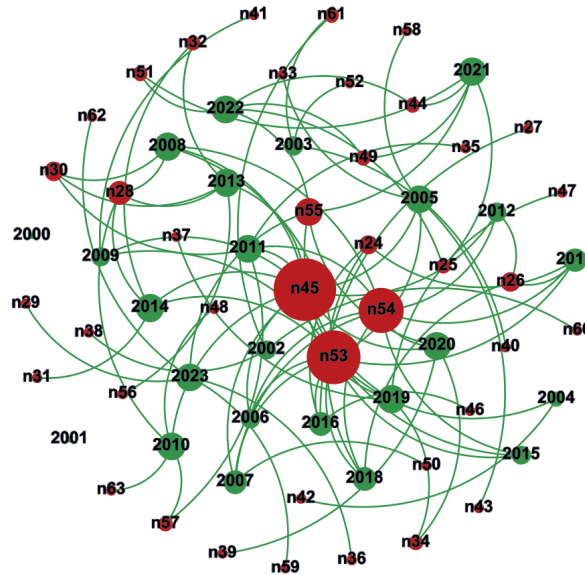


Figure 5.15: Temporal Network of Key Research Themes in Community 41: Labels in red and Years in green (2000–2023)

The centrality of several keyword nodes—n38 (“Decision Support”), n40 (“Medical Decision Support”), and n53 (“Medical Decision Support”)—identifies decision support as the most critical and persistent concept. The core objective is to develop systems that effectively support human decision-making, mostly in clinical and home environments. This main theme is connected to n56 (“Healthcare Knowledge and Information Technology”). Also, the centrality of n55 (“Smart Home Ambient Activity”) right next to the DSS hubs indicates that a core, long-term goal involves applying these systems to monitor and support people in their daily environments. The community’s evolution is marked by the continuous update of its analytical framework, enabling TC into emerging application domains. The early and mid-years focused heavily on foundational AI methods required for complex reasoning and structured problem-solving, exemplified by nodes like n45 (“Case-Based Reasoning”). The later years reflect a decisive methodological shift toward data-intensive applications, where the community’s DSS framework is applied to modern sensing and prediction problems. Significantly, a distinct cluster of mental health technology emerges in the later years (near 2021). Nodes like n51 (“Digital Mental Health Tools”), n59 (“Virtual Reality Mental Health Therapy”), and n49 (“COVID-19 Mental Health Impact”) show a recent, and specialized application of their core decision support and monitoring expertise toward emerging psychological

and public health challenges. This analysis validates that Community 41 functions as a methodological hub that repeatedly achieved TC by integrating new techniques to solve complex, high-impact decision-making problems in diverse application domains.

5.2.4 Quantum Machine Learning

Community 1160, initially recognized for “Quantum Machine Learning” underwent a significant transformation in 2009 through a TC convergence with Community 238, which specialized in bioinformatics applications such as “Protein Crystallization and Protein Secondary Structure Prediction” and “Vaccine Design and Epitope Analysis” (Fig. 5.16). This fusion created a new interdisciplinary Community 1160 by 2010, blending quantum machine learning’s computational power with biological and astroinformatics expertise. The redefined community’s labels include “Quantum Machine Learning”, “Astroinformatics and Machine Learning”, and “Prediction Metabolomics”. In 2010, Community 1160 further evolved by merging with Community 336, which specialized in computational healthcare with expertise in areas such as “Genome-Wide Disease Association Studies” and “Breast Cancer Machine Learning Analysis”. This merger resulted in an evolved Community 336 in 2011, which centred on “Cancer Detection and Prognosis”, “Genomics and Medical Data Analysis”, and retained its “Astronomical Data” roots. Despite a predominant focus on healthcare applications, Community 336 maintained its foundation in quantum machine learning and astroinformatics, demonstrating the adaptability of methodological cores across applied domains. By

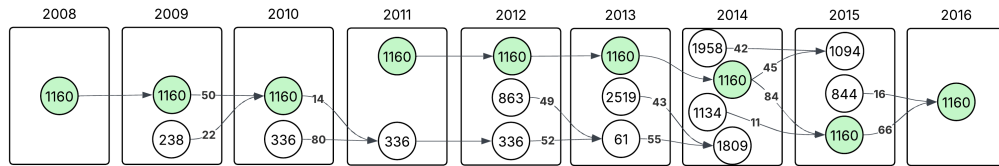


Figure 5.16: Trajectory of Community 1160 from 2008 to 2016.

2012, Community 336 had a convergence with Community 863, leading to the creation of Community 61 in 2013. This new community focused on “Galaxy Transient Survey and Classification” and “Cancer Cell Protein and Molecular Conformation”, showcasing a synergy between astronomical applications and advanced data analysis methodologies. In 2013, Community 2519, known for

“Pulsar Surveys” and machine learning applications in astrophysical discoveries, merged with Community 61 to form Community 1809 in 2014. This new entity concentrated on “Pulsar Candidate Classification”, “Radio Pulsar Survey”, and “Synoptic Sky Survey”, effectively integrating broad machine learning methodologies with specific astrophysical applications. Community 1809, then expanded in the mid-2010s to integrate advanced “Clustering and Predictive Methodologies” for broader astronomical surveys. This culminated in 2020 and 2022 with a complete domain-agnostic shift toward developing generalizable computational methods (including Wavelet and Graph-based ML) for complex signal analysis across physical, biological, and engineered systems.

In 2014, Community 1160 (initially QML focus) diverged and merged. One segment of Community 1160 merged with Community 1958 (a group centered on “Topological Quantum Error Correction”, and “Surface and Color Code Analysis”), creating Community 1094 in 2015, which focused on the foundational engineering of “Adaptive Phase Estimation and Bayesian Metrology”, and “Quantum Computing for Stock Data Analysis”. Another segment of Community 1160 had a TC with Community 1134 focused on “Sparse Function Learning and Modeling”, and “Auction Game Theory with Human Agents”. The resulting Community 1160 in 2015 expanded its scope to include “Quantum Machine Learning and Computing”, “Fairness, Privacy, and Domain Applications”, and “Optimization and Control”. In 2015, Community 1160 further enhanced its robustness through a TC with Community 844 (“Email Spam Filtering and Detection”, “Robust Support Vector Machines”, and “Gene Expression and Cancer Network Analysis”). The new Community 1160 in 2016 was concentrated on the “Methodology of Graphical Models” and “Structure Learning”, with applications in genomics. In 2017, Community 1160 underwent another TC with Community 535 (“Molecular Drug-Protein Interaction Prediction”, “Attributed Network Embedding”, and “Collaborative Filtering Recommendation”), deepening its capabilities in advanced modeling. Finally, in

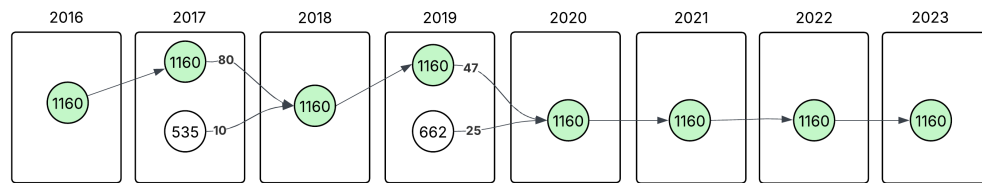


Figure 5.17: Trajectory of Community 1160 from 2016 to 2023.

2019, Community 1160 merged with Community 662, a group concentrating on “ECG Arrhythmia Classification”, and “Tactile Object Sensing”. The resulting Community 1160 in 2020 represents labels such as “Domain Adaptation, Transfer Learning, and Generalization”, “Ensemble Learning and Multi-Classifer System Architectures”, and “Biomedical Robotics, Exoskeleton Control, and sEMG Signal Processing”. Fig. 5.17 shows the trajectory of Community 1160 from 2016 to 2023. The complete list of topics and their associated top keywords for Community 41 and all interacting communities across the study period is provided in Appendix B.4, Table B.4.

Community 1160: Network Visualization and Thematic Evaluation

The visualization of Community 1160’s network, see Fig. 5.18, reveals a highly sophisticated research community primarily dedicated to methodological advancements in machine learning. Its trajectory demonstrates a concerted effort to solve the core challenges associated with model deployment, generalizability, and future computing in complex, real-world settings. The complete node-label mapping for this network is provided for reference in the Appendix C, Table C.4.

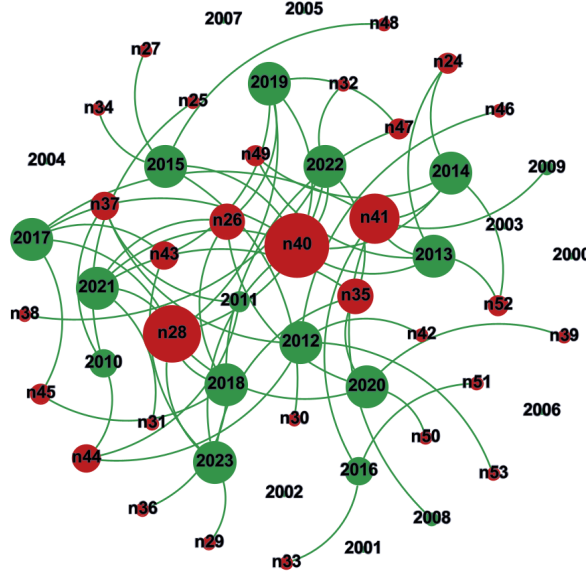


Figure 5.18: Temporal Network of Key Research Themes in Community 1160: Labels in red and Years in green (2000–2023)

The functional identity of Community 1160 is defined by its focus on creating robust algorithms that function reliably under non-ideal, shifting conditions. The tight cluster involving the

years 2018, 2019, 2021, and 2022 marks a period of maximal integrated research activity. At the very core sit the keyword hubs n40 (“Stochastic Nonconvex Optimization”) and n28 (“Unsupervised Domain Adaptation”). The high density of connections across the network confirms that these core methodologies, especially Domain Adaptation, are continuously relevant. QML represents the community’s definitive forward-looking specialization, reflecting an effort to explore the theoretical and computational limits of machine learning algorithms. The focused cluster of QML nodes, including n41 (“Quantum Machine Learning”), n44 (“Quantum Machine Learning and Estimation”), n46 (“Quantum K-Means Clustering”), and n53 (“Quantum Reinforcement Learning Control”), shows a commitment to fundamentally researching how quantum computing can revolutionize the algorithmic efficiency. A major application area of this community, is system reliability and maintenance. This is evident in topics such as n32 (“Remaining Useful Life (RUL)”), n26 (“Machinery Bearing Fault Diagnosis”), and n24 (“ML-Based Structural Steel Damage”). The community’s generalization expertise is directly applied to challenging health data environments, as seen in n50 (“ECG and Heart Sound Arrhythmia”) and n34 (“AI for Heart Disease Patients”). The earliest connections point to an enduring interest in foundational biological modeling, exemplified by n37 (“Metabolic Pathway and Protein Prediction”).

Chapter 6

Conclusion

The convergence of scientific knowledge serves as a pivotal driver for the emergence of new technologies. By understanding and analyzing this process, we can provide decision-makers and planners with the tools to strategically allocate resources and anticipate technological tipping points. This paper presents a framework that utilizes citation networks and topology clustering to uncover the convergence of scientific knowledge through publication data. Leveraging large language models and unsupervised machine learning techniques, it offers a comprehensive analysis of the dynamic evolution of scientific knowledge in the field of artificial intelligence. Our findings illustrate that scientific convergence is a structured yet non-linear process driven by meta-technologies such as AI, which act as cross-disciplinary catalysts. Within this framework, we identified three key patterns—Generative, Transformative, and Divergent—each playing a dynamic role in shaping new fields and technologies. The four communities we analyzed validate this framework, as they share a common growth pattern while highlighting distinct strategic pathways. Each community started with a core methodology and significantly impacted critical applications, embodying the paradigm of “use-inspired basic research”, where practical challenges not only apply theoretical concepts but also drive theoretical advancements [Williams \(2008\)](#). This interaction with real-world problems actively enhanced and broadened existing methodological knowledge rather than merely consuming it. This observation aligns with the notion that addressing complex practical problems, which existing theories cannot fully resolve, often creates conditions for innovative theoretical development [Baskerville \(2007\)](#). Our analysis revealed several key drivers for the creation of new disciplines

and technologies. Fields often merge when they share complementary frameworks or methods that can be combined to tackle larger problems more effectively. The demand for complex solutions encourages the integration of various fields of expertise, for example demonstrated by the merger of quantum machine learning with bioinformatics to address biological challenges. Moreover, developments in one field often provide tools or data that another field can leverage, such as the convergence of medical imaging with Bayesian probabilistic methods to enhance medical image analysis. Our framework offers a powerful lens for both describing past dynamics and predicting future trends in scientific convergence. By identifying and predicting emerging fields, we propose a data-driven framework that allows stakeholders to proactively target investments and foster the next generation of scientific innovation. This approach, which can be applied to other scientific domains, shifts the focus from observing established fields to tracking the dynamic flow of methods and problems, ultimately improving the landscape of scientific advancement. Our analysis shows that scientific convergence is a structured yet non-linear process, driven by meta-technologies such as AI that act as cross-disciplinary catalysts. Within this process, we identify three measurable patterns of convergence, Generative, Transformative, and Divergent, each playing a dynamic role in shaping the emergence of new fields and technologies.

Chapter 7

Limitations and Future Work

While this study offers a novel framework for mapping and analyzing the convergence of scientific knowledge, it is subject to limitations inherent in its design, which consequently inform a compelling agenda for future research.

Limitations

- **Publication and Citation Bias:** Our reliance on publication and citation patterns is subject to a form of publication bias. Highly novel or radical ideas may be underrepresented in the citation network until they gain sufficient publications and citations, potentially delaying or preventing their detection by our methodology.
- **Temporal Granularity:** Our use of annual cumulative analysis, while effective for capturing major convergence trends, may obscure more rapid, micro-level interactions and fusions occurring on a sub-annual timescale. The chosen temporal granularity may therefore miss nuanced dynamics that evolve more swiftly, suggesting a trade-off between macro-level trend detection and high-resolution dynamic analysis.
- **Scope and Impact Translation:** Identifying a scientific convergence event does not necessarily equate to predicting its market success or societal impact. The transition from recognized convergence in academic literature to a viable technology or commercial product involves

numerous external factors—such as regulatory challenges, economic viability, and societal acceptance—which are beyond the scope of our citation-based analysis.

Future Work

These acknowledged limitations not only delineate the boundaries of the current findings but also define a compelling agenda for future research.

- **Predictive Modelling:** A promising extension involves the development of predictive modelling techniques. By using identified historical convergence patterns as a training set, future research could leverage machine learning to predict potential areas of technological fusion, offering stakeholders an early-warning system for emerging technological paradigms.
- **Global Benchmarking:** Applying this analytical framework to the scientific outputs of other major innovation hubs, such as the United States, the European Union, and China, would allow for comparative analysis. This would clarify whether Canada's convergence pathways are unique or part of a broader global trend, helping to identify specific national strengths, weaknesses, and strategic gaps in the AI research landscape.
- **Integrate Patent and Economic Data:** Future research could integrate patent data alongside publications to bridge the gap between scientific discovery and technological application, providing a more holistic view of the innovation pipeline. Additionally, exploring the integration of social and economic data could offer insights into the factors influencing the translation of converged scientific fields into impactful technologies or products.
- **Expanded Temporal Granularity:** Finally, expanding the temporal granularity of the analysis to capture more frequent data points (e.g., quarterly or monthly) could help uncover micro-level interactions and rapid fusions, providing a more detailed understanding of the true convergence dynamics at play.

Appendix A

Fast-Newman Clustering Results

Table A.1: Table of Communities Detected by FN Each Cumulative Year

Year	Number of Nodes	Number of Communities
2000	6,037	169
2001	18,093	337
2002	28,630	507
2003	39,081	697
2004	57,473	901
2005	80,793	1,091
2006	108,511	1,297
2007	126,239	1,497
2008	155,801	1,749
2009	216,751	1,894
2010	227,642	2,113
2011	243,579	2,325
2012	274,656	2,539
2013	309,305	2,741
2014	337,426	2,960

Continued on next page

Year	Number of Nodes	Number of Communities
2015	383,112	3,201
2016	433,307	3,338
2017	510,738	3,620
2018	599,049	3,877
2019	706,766	4,313
2020	857,012	4,767
2021	980,623	5,380
2022	1,078,216	6,281
2023	1,132,320	8,101

Appendix B

Detailed Thematic Evolution and Keywords

B.1 Thematic Data for Communities Interacting with Community 15

Table B.1: Community 15: Thematic Evolution of Key Communities. Note: The column Year indicates the first year the respective community was detected in the cumulative network or the first year it was recorded as being involved in a convergence/divergence event with Community 15.

Community	Year	Topics	Top Keywords
170	2001	Automated and Temporal Planning	planning, search, heuristic, temporal, competition
170	2001	Sokoban Puzzle Solving with Prolog	sokoban, optimal, solving, solving sokoban, problem
170	2001	Durative and Interactive Planning	action, durative, durative action, effect, learning
170	2001	—	—
170	2001	—	—

Continued on next page

Community	Year	Topics	Top Keywords
340	2003	Star Craft Strategy	game, realtime, strategy, realtime strategy, strategy game
340	2003	Deep Reinforcement Learning in Real-Time Strategy Games	learning, reinforcement learning, game, reinforcement, realtime strategy
340	2003	—	—
340	2003	—	—
340	2003	—	—
93	2005	Lifted Probabilistic Relational Inference	probabilistic, inference, lifted, relational, logic
93	2005	Markov Decision Processes	decision, markov decision, decision process, mdps, learning
93	2005	Generalized Planning	planning, generalized, plan, generalized planning, planner
93	2005	CP-Nets Dominance and Aggregation	cpnets, dominance, dominance testing, complexity, aggregation
93	2005	Situation Calculus and Action Progression	calculus, situation, situation calculus, action, progression
592	2005	Multi-Agent Path Planning	path, multiagent, planning, finding, multiagent path
592	2005	Satisfiability-Based Path Finding	satisfiability, path finding, delivery, path, approach
592	2005	—	—
592	2005	—	—

Continued on next page

Community	Year	Topics	Top Keywords
592	2005	—	—
126	2006	Multi-Agent Path Planning	path, multiagent, finding, multiagent path, path finding
126	2006	Warehouse Path Planning	warehouse, warehouse problem, path, path planning, lifelong multiagent
126	2006	Multi-Agent Pickup and Delivery	pickup delivery, pickup, delivery, multiagent pickup, multiagent
126	2006	Reinforcement Learning in Decision Processes	decision, learning, reinforcement, reinforcement learning, decision process
126	2006	Situation Calculus and Action Reasoning	calculus, situation, situation calculus, action, reasoning
217	2007	RoboCup Soccer Simulation	soccer, robocup, keepaway, simulation, robot
217	2007	Inverse Reinforcement Learning	inverse, inverse reinforcement, reinforcement, reinforcement learning, learning
217	2007	Multi-Agent Reinforcement Learning	multiagent, multiagent reinforcement, learning, agent, environment
217	2007	Lifelong Learning with Temporal Abstraction	demonstration, abstraction, learning, lifelong, temporal abstraction

Continued on next page

Community	Year	Topics	Top Keywords
217	2007	Markov Decision Processes	process, markov, markov decision, decision process, decision
1359	2007	Bayesian Optimization	optimization, bayesian, bayesian optimization, search, learning
1359	2007	Bipedal Robot Gait Learning	gait, learning, robot, locomotion, bipedal
1359	2007	Active Learning in Robotics	learning, active, active learning, robot, learning robot
1359	2007	Gaussian Process Bandits	bandit, gaussian process, gaussian, process, process bandit
1359	2007	—	—
219	2008	Real-Time Strategy Games	game, strategy, strategy game, realtime, realtime strategy
219	2008	RoboCup Soccer Simulation	soccer, robocup, robot, robocup soccer, simulation
219	2008	Multi-Agent Reinforcement Learning	multiagent, multiagent reinforcement, learning, reinforcement, reinforcement learning
219	2008	Markov Decision Processes	process, markov, decision process, markov decision, decision
219	2008	Reinforcement Learning with Demonstration and Abstraction	demonstration, learning, reinforcement, reinforcement learning, abstraction

Continued on next page

Community	Year	Topics	Top Keywords
680	2008	Bayesian Optimization	optimization, bayesian, bayesian optimization, search, process
680	2008	Bipedal Robot Gait Learning	gait, robot, locomotion, learning, bipedal
680	2008	Active Preference Learning	preference, learning, active, active learning, choice
680	2008	Billiards and Pool Game Strategy	billiards, shot, game, billiard, pool
680	2008	Multi-Agent Learning and Equilibrium	multiagent, limitation, equilibrium, learning, agent
16	2011	Reinforcement Learning with Policy and Stat	learning, reinforcement, reinforcement learning, policy, state
16	2011	Gait Detection and Sensor-Based Control	gait, detection, sensor, event, control
16	2011	Social Coalition Formation in Games	game, coalition, social, formation, coalition formation
16	2011	Spoken Dialogue and User Intention	dialogue, user, intention, spoken, spoken dialogue
16	2011	Altruistic Hedonic Games	hedonic, hedonic game, game, altruistic, altruistic hedonic
288	2014	Language Models and Learning	language, model, language model, learning, understanding
288	2014	Multi-Agent Probabilistic Planning with POMDPs	planning, pomdps, decision, multiagent, probabilistic

Continued on next page

Community	Year	Topics	Top Keywords
288	2014	Commonsense Reasoning and Question Answering	commonsense, commonsense reasoning, reasoning, question, answering
288	2014	Ontology-Based Semantic Knowledge in Manufacturing	ontology, ontologybased, semantic, knowledge, manufacturing
288	2014	Cognitive Theory of Mind	cognitive, thinking, cognition, theory, mind
88	2015	Multi-Agent Epistemic Planning with BDI	agent, multiagent, epistemic, bdi, epistemic planning
88	2015	Belief Revision and Change Calculus	belief, revision, belief revision, calculus, belief change
88	2015	Multi-Winner Voting Rules and Elections	voting, election, voting rule, rule, multiwinner
88	2015	Software Product Line Requirements	software, product, product line, line, requirement
88	2015	Planning and Plan Execution	plan, planning, planner, execution, problem
90	2016	Technology for Older Adult Aging	voting, election, rule, voting rule, multiwinner
90	2016	Alzheimer's and Dementia	dementia, alzheimer, people, disease, people dementia
90	2016	POMDP Planning with Point-Based Value Iteration	pomdps, pomdp, iteration, pointbased, value iteration

Continued on next page

Community	Year	Topics	Top Keywords
90	2016	Assistive Technology for Intellectual Disability	belief, revision, belief revision, belief change, change
90	2016	Ambient Assisted Living	constraint, constraint acquisition, acquisition, decomposition, constraint satisfaction
14	2018	Neural Networks and Deep Learning	neural network, neural, gradient, deep learning, natural gradient
14	2018	Cooperative Multi-Agent Reinforcement Learning	multiagent reinforcement, multiagent, cooperative, cooperative multiagent, learning multiagent
14	2018	Equilibrium in Imperfect Extensive-Form Games	equilibrium, extensiveform, game, extensiveform game, imperfect
14	2018	Numeric and Classical Planning	plan, planning, planner, numeric, classical
14	2018	Multi-Winner Voting and Election Rules	voting, election, rule, voting rule, multiwinner
132	2020	Skin Cancer and Melanoma Detection	skin, skin lesion, melanoma, skin cancer, lesion
132	2020	Autism Spectrum Disorder Diagnosis	autism, autism spectrum, spectrum disorder, spectrum, disorder
132	2020	Lung Cancer and Nodule Classification	lung, lung cancer, nodule, cell lung, nonsmall
<i>Continued on next page</i>			

Community	Year	Topics	Top Keywords
132	2020	Acute Ischemic Stroke Analysis	stroke, ischemic, ischemic stroke, acute ischemic, acute
132	2020	Alzheimer's Disease Diagnosis and Classification	alzheimer, alzheimer disease, disease, diagnosis alzheimer, classification alzheimer
89	2021	Prostate Cancer Biopsy and Gleason Grading	prostate, prostate cancer, biopsy, cancer, gleason
89	2021	Skin Cancer and Melanoma Detection	skin, skin lesion, melanoma, skin cancer, lesion
89	2021	Autism Spectrum Disorder Diagnosis	autism, autism spectrum, spectrum disorder, spectrum, disorder
89	2021	Schizophrenia and First-Episode Psychosis Analysis	schizophrenia, psychosis, firstepisode, firstepisode psychosis, patient schizophrenia
89	2021	Cardiac MRI and Left Ventricle Analysis	cardiac, ventricle, left, left ventricle, cardiac mri
504	2022	Epileptic Seizure Detection and Epilepsy Analysis	seizure, epileptic, epileptic seizure, seizure detection, epilepsy
504	2022	Sleep Stage Classification	sleep, sleep stage, stage, stage classification, sleep staging
504	2022	Traffic Flow Prediction	traffic, traffic flow, flow, flow prediction, prediction
504	2022	Driver Behavior Analysis	driver, behavior, driving, driver behavior, driving behavior

Continued on next page

Community	Year	Topics	Top Keywords
504	2022	EEG-Based Emotion Recognition	emotion, emotion recognition, eegbased emotion, eegbased, recognition

B.2 Thematic Data for Communities Interacting with Community 5

Table B.2: Community 5: Thematic Evolution of Key Communities. Note: The column Year indicates the first year the respective community was detected in the cumulative network or the first year it was recorded as being involved in a convergence/divergence event with Community 5.

Community	Year	Topics	Top Keywords
118	2002	Software Fault Prediction	prediction, fault, software, defect, fault prediction
118	2002	Software Effort Estimation	estimation, effort, software, software effort, effort estimation
118	2002	Component Reuse and Repository Search	reuse, component, browsing, search, repository
118	2002	Software Quality Classification	quality, software quality, software, classification, quality classification
118	2002	Artificial Neural Networks	network, neural network, neural, artificial, artificial neural

Continued on next page

Community	Year	Topics	Top Keywords
115	2003	Software Defect Prediction and Reliability	defect prediction, predicting defectprone, software defect, defect detection, defectprone software, defect data, fault prediction, software reliability, defectprone, learning software
115	2003	fMRI-Based Functional and Spatial Activation Analysis	fmri, tc, activation, spatial, functional
115	2003	Genetic Programming for Software Quality Classification	quality software, software quality, quality classification, improve software, genetic programming, genetic classifier, software object, classification genetic, quality object, decision tree
115	2003	Rule-Based Software Quality Modeling and Analysis	software quality, quality classification, quality analysis, quality prediction, quality estimation, software measurement, quality modeling, software engineering, learning software, rulebased software
<i>Continued on next page</i>			

Community	Year	Topics	Top Keywords
115	2003	Semantic Software Component Retrieval and Reuse	reuse repository, interoperation reuse, component retrieval, semantic interoperation, software repository, relevancy semantic, repository information, retrieval, semantic, repository
130	2003	Case-Based Reasoning	reasoning, casebased, case, casebased reasoning, base
130	2003	—	—
130	2003	—	—
130	2003	—	—
130	2003	—	—
625	2004	Brain Functional Analysis	brain, machine, machine learning, functional, learning
625	2004	Feature Selection for Classification and Detection	selection, feature, feature selection, classification, detection
625	2004	Radiomics for Liver Cancer Cell	image, radiomics, cancer, liver, cell
625	2004	Graph Neural Networks and Kernels	graph, graph neural, neural, kernel, network
625	2004	Smartphone Sensor-Based Movement and Cybersickness Detection	sensor, movement, cybersickness, smartphone, activity
341	2004	Fuzzy Neural Networks with Polynomial Features	fuzzy, network, neural, neural network, polynomial

Continued on next page

Community	Year	Topics	Top Keywords
341	2004	ECG-Based Arrhythmia Classification and Disease Detection	ecg, classification, arrhythmia, machine, disease
341	2004	—	—
341	2004	—	—
341	2004	—	—
235	2005	Partial Discharge Pattern Recognition	discharge, partial, partial discharge, pattern, recognition
235	2005	Fuzzy Programming for Assignment Problems	assignment, assignment problem, problem, fuzzy, programming
235	2005	—	—
235	2005	—	—
235	2005	—	—
213	2005	Machine Learning for Disease Detection in Patients	machine, machine learning, learning, disease, patient
213	2005	Protein-Protein Interaction Sequence Analysis	protein, interaction, proteinprotein interaction, proteinprotein, sequence
213	2005	Imbalanced Data and Class Imbalance Handling	imbalanced, imbalanced data, data, class, imbalance
213	2005	IoT Anomaly and Attack Detection	anomaly, anomaly detection, detection, iot, attack
<i>Continued on next page</i>			

Community	Year	Topics	Top Keywords
213	2005	Chest X-Ray Lung Image Analysis	lung, chest, xray, chest xray, xray image
316	2006	Machine Learning for Predictive Modeling	prediction, machine, learning, machine learning, data
316	2006	Machine Learning for Brain Disorder Analysis	brain, disorder, machine, machine learning, functional
316	2006	Machine Learning for Predictive Inference	machine, prediction, machine learning, learning, inf
316	2006	Cross-Validation and Error Estimation	crossvalidation, variance, error, estimator, kfold
316	2006	Decision Tree Ensembles with Bagging	tree, decision, decision tree, ensemble, bagging
212	2007	Spam Email Filtering and Detection	machine, machine learning, learning, disease, patient
212	2007	Machine Learning for Patient Outcome Prediction	maintenance, railway, wheel, fault, vehicle
212	2007	Imbalanced Data Classification	imbalanced, imbalanced data, data, class, imbalance
212	2007	Climate Change Impact and Susceptibility Analysis	anomaly, anomaly detection, detection, iot, attack
212	2007	Gene Association Networks and Prediction	susceptibility, landslide, climate, change, climate change
198	2009	Software Defect Prediction	software, defect, defect prediction, software defect, prediction

Continued on next page

Community	Year	Topics	Top Keywords
198	2009	Land Cover Mapping and Change Detection	forest, land, cover, mapping, change
198	2009	Machine Learning for Heart Risk Patient Care	risk, heart, patient, machine learning, care
198	2009	Manufacturing Fault Diagnosis and Detection	fault, fault diagnosis, diagnosis, fault detection, manufacturing
198	2009	Credit Card Fraud Detection	fraud, fraud detection, credit card, card, credit
80	2010	Protein Interaction Site Prediction	gene, protein, interaction, prediction, site
80	2010	Software Defect Prediction	software, defect, defect prediction, software defect, prediction
80	2010	Railway Prognostic and Predictive Maintenance	prognostic, maintenance, failure, railway, predictive maintenance
80	2010	Text Classification and Categorization	text, text classification, categorization, topic, text categorization
80	2010	Machine Learning for Electronic Health and Survival Analysis	health, machine learning, electronic, care, survival
608	2010	Clinical Decision Support Systems	clinical, decision, support, decision support, medical
608	2010	Gene Data Mining and Analysis	data, gene, data mining, mining, set
608	2010	Acute Appendicitis and Abdominal Pain Diagnosis	acute, appendicitis, acute appendicitis, abdominal, pain

Continued on next page

Community	Year	Topics	Top Keywords
608	2010	Swallowing Sound Signal Analysis	swallowing, sound, swallowing sound, signal, feature
608	2010	—	—
58	2013	Heart Disease and Cancer Prediction	disease, heart, prediction, health, cancer
58	2013	Sequential Pattern Mining	sequential, sequential pattern, pattern, pattern mining, mining
58	2013	Association Rule Mining and Classification	association, association rule, rule, rule mining, classification
58	2013	Associative Classification	associative, associative classification, classification, associative classifier, classifier
58	2013	Privacy Preserving Data Mining	privacy, preserving, privacy preserving, sensitive, hiding
1684	2013	Respiratory and Lung Sound Classification	sound, classification, respiratory, lung, lung sound
1684	2013	Wheezing Detection for Asthma	wheeze, wheezing, detection, asthma, sound
1684	2013	Snoring Signal Detection in Sleep	snore, snoring, sleep, signal, detection
1684	2013	—	—
1684	2013	—	—
125	2014	Respiratory and Lung Sound Classification	sound, respiratory, lung, respiratory sound, classification

Continued on next page

Community	Year	Topics	Top Keywords
125	2014	Fuzzy Decision Support for Diagnosis	decision, fuzzy, diagnosis, support, decision support
125	2014	Texture-Based Image Classification	texture, classification, texture classification, image, local
125	2014	Glaucoma Progression and Visual Field Analysis	glaucoma, progression, visual field, visual, field
125	2014	Diabetic Retinopathy and Tear Biomarkers	diabetic, diabetic retinopathy, retinopathy, tear, biomarkers
77	2016	Image Quality Analysis	machine, machine learning, learning, image, quality
77	2016	Smart Grid Attack Detection	attack, detection, grid, smart, smart grid
77	2016	Continuous Attribute Discretization Methods	discretization, discretization method, attribute, continuous, continuous attribute
77	2016	Bayesian Network Classifiers	bayesian, bayesian network, network, classifier, learning bayesian
77	2016	Social Text Document Recommendation and Topic Modeling	social, text, document, recommendation, topic
75	2017	Physiological Signal-Based Emotion Recognition	emotion, emotion recognition, recognition, signal, physiological
<i>Continued on next page</i>			

Community	Year	Topics	Top Keywords
75	2017	Cancer Detection	disease, machine, machine learning, learning, cancer
75	2017	Naive Bayes Classifiers	bayes, naive, naive bayes, classifier, nave
75	2017	Element Mapping	machine, element, machine learning, learning, mapping
75	2017	Wireless Network Intrusion Detection	detection, wireless, network, intrusion, intrusion detection
26	2018	Crime Prediction	crime, prediction, crime prediction, machine, machine learning
26	2018	Wireless Sensor Network Detection	wireless, network, detection, sensor, wireless sensor
26	2018	Causal Relation and Event Extraction	causality, causal, extraction, relation, event
26	2018	Physiological Signal-Based Emotion Recognition	emotion, physiological, emotion recognition, signal, recognition
26	2018	Bayesian Network Classifiers	bayesian, bayesian network, network, classifier, learning bayesian
285	2018	PET-CT Tumor Segmentation	segmentation, pet, image, petct, tumor
285	2018	Deep Neural Networks	neural, neural network, network, deep, deep neural
<i>Continued on next page</i>			

Community	Year	Topics	Top Keywords
285	2018	Cervical Cancer Diagnosis	cancer, cervical, cervical cancer, diagnosis, intelligence
285	2018	Gene Annotation and Protein Expression Splicing	gene, annotation, protein, expression, splicing
285	2018	Parkinson's Disease Clinical	parkinson, parkinson disease, disease, clinical, motor
1852	2019	Deepfake Video Detection	deepfake, deepfake detection, deepfake video, video, detection
1852	2019	Social Media Bot Detection	bot, bot detection, social bot, social, twitter
1852	2019	Deep Learning for Fake News Detection	deep, deep learning, news detection, fake news, news
1852	2019	Rumor Detection in Social Networks	rumor, rumor detection, social network, network, network rumor
1852	2019	Facial Video Forgery and Deepfake Detection	face, facial, video, face forgery, deepfake
57	2020	Mental Health and Anxiety During COVID-19	mental, psychological, covid19 pandemic, anxiety, pandemic
57	2020	Twitter Sentiment and Topic Analysis	sentiment, sentiment analysis, twitter, topic, analysis
57	2020	Chest X-Ray Image Analysis	chest, chest xray, xray, xray image, image
57	2020	Pneumonia Detection in Chest X-Ray Images	pneumonia, lung, chest, xray, image

Continued on next page

Community	Year	Topics	Top Keywords
57	2020	Drug Repurposing and Repositioning	drug, repurposing, drug repurposing, repositioning, drug repositioning
520	2020	Collaborative Filtering Recommendation	recommendation, collaborative filtering, collaborative, filtering, recommender
520	2020	Graph Neural Networks	graph neural, neural network, neural, network, graph
520	2020	EEG-Based Brain Emotion Recognition	brain, emotion, emotion recognition, eeg, functional
520	2020	Graph Anomaly Detection	anomaly, anomaly detection, detection, graph anomaly, detection graph
520	2020	Attributed Network Embedding	network embedding, embedding, attributed network, attributed, network
1985	2020	Localized Prostate Cancer and Biochemical Recurrence	prostate, prostate cancer, cancer, biochemical, localized
1985	2020	Glaucoma Detection in Fundus Images	glaucoma, fundus, image, detection, fundus image
1985	2020	Molecular Breast Cancer Pathology	breast, breast cancer, molecular, cancer, pathology

Continued on next page

Community	Year	Topics	Top Keywords
1985	2020	Tumor-Infiltrating Lymphocytes in Breast Cancer	lymphocyte, lymphocyte breast, tumorinfiltrating lymphocyte, tumorinfiltrating, breast
1985	2020	Chronic Kidney Disease Analysis	kidney, kidney disease, chronic kidney, chronic, machine
5148	2021	Wind Power Energy Storage	energy, storage, wind, power, energy storage
5148	2021	—	—
5148	2021	—	—
5148	2021	—	—
5148	2021	—	—
3474	2021	Hydrogen Storage in Alloys via Electrolysis	water, hydrogen, alloy, electrolysis, storage
3474	2021	Smart Energy Analysis for Hydrogen Production	hydrogen, energy, production, analysis, smart
3474	2021	Hydrogen Evolution Reaction	hydrogen, evolution, hydrogen evolution, reaction, evolution reaction
3474	2021	—	—
3474	2021	—	—
2889	2022	Topological Data Analysis	data, topological, data analysis, analysis, topological data
2889	2022	Persistent Homology in Time Series	homology, persistent homology, persistent, series, time series

Continued on next page

Community	Year	Topics	Top Keywords
2889	2022	—	—
2889	2022	—	—
3713	2022	Vaccine Development	vaccine, development, review, vaccine development, virus
3713	2022	Helminth Image Detection	image, soiltransmitted, soiltransmitted helminth, helminth, detection
3713	2022	—	—
3713	2022	—	—
3713	2022	—	—
2111	2022	Leukemia Blood Image Classification	blood, learning, classification, image, leukemia
2111	2022	Flow Cytometry Cell Data Analysis	cytometry, flow, flow cytometry, data, cell
2111	2022	—	—
2111	2022	—	—
2111	2022	—	—
291	2022	Crop Nitrogen and Yield Fertilizer Optimization	soil, crop, nitrogen, yield, fertilizer
291	2022	Municipal Solid Waste Management	waste, solid waste, solid, municipal, municipal solid
291	2022	Biochar Adsorption and Soil Remediation	biochar, removal, adsorption, remediation, adsorbent

Continued on next page

Community	Year	Topics	Top Keywords
291	2022	Gas Turbine Fault Diagnosis	fault, diagnosis, fault diagnosis, turbine, gas turbine
291	2022	Diesel Engine Combustion and Ignition Control	engine, combustion, diesel, ignition, control
3454	2023	Wind Power Energy Storage	energy, wind, storage, energy storage, power
3454	2023	Proton Exchange Membrane Water Electrolysis	membrane, membrane water, exchange, exchange membrane, water
3454	2023	Green Hydrogen Production	hydrogen, production, green, green hydrogen, hydrogen production
3454	2023	PEM Fuel Cells	fuel cell, fuel, cell, pem fuel, pem
3454	2023	Polymer Electrolyte Membrane Fuel Cells	membrane fuel, fuel cell, fuel, cell, membrane

B.3 Thematic Data for Communities Interacting with Community 41

Table B.3: Community 41: Thematic Evolution of Key Communities. Note: The column Year indicates the first year the respective community was detected in the cumulative network or the first year it was recorded as being involved in a convergence/divergence event with Community 41.

Community	Year	Topics	Top Keywords
590	2002	Healthcare	health, care, medical, patient, clinical, health system
590	2002	—	—

Continued on next page

Community	Year	Topics	Top Keywords
590	2002	—	—
590	2002	—	—
590	2002	—	—
84	2003	Automated Multi-Issue Negotiation Agents	negotiation, agent, automated, automated negotiation, multiissue
84	2003	Market-Based Negotiation Processes	negotiation, process, market, negotiation process, type
84	2003	—	—
84	2003	—	—
84	2003	—	—
2	2004	AI-Driven Remediation Management	artificial, remediation, intelligence, artificial intelligence, management
2	2004	Natural Gas Pipeline Optimization	gas, optimization, pipeline, natural gas, natural
2	2004	Fuzzy Spatial and Geographic Information Relations	spatial, relation, information, fuzzy, geographic
2	2004	Ontology-Based Knowledge Modeling and Applications	knowledge, ontology, modeling, application, tool
2	2004	—	—
22	2004	Shop Scheduling Problems	scheduling, problem, shop, job, job shop

Continued on next page

Community	Year	Topics	Top Keywords
22	2004	Holonic Manufacturing Control Architectures	control, manufacturing, architecture, holonic, control architecture
22	2004	Dynamic Multi-Agent Manufacturing Scheduling	scheduling, manufacturing, dynamic, dynamic scheduling, multiagent
22	2004	Distributed Collaborative Design	collaborative, design, collaborative design, distributed, distributed collaborative
22	2004	Multi-Agent Manufacturing Planning and Control	planning, planning control, manufacturing, multiagent, manufacturing planning
277	2005	Healthcare Knowledge and Technology	knowledge, health, healthcare, care, technology
277	2005	Medical Case-Based Reasoning	reasoning, case, medical, casebased, casebased reasoning
277	2005	Student Reflective Learning and Practice	reflection, learning, student, practice, discussion
277	2005	Adolescent Idiopathic Scoliosis	scoliosis, idiopathic scoliosis, idiopathic, adolescent idiopathic, adolescent
277	2005	Personal Digital Assistant Applications	digital, personal digital, digital assistant, assistant, personal
<i>Continued on next page</i>			

Community	Year	Topics	Top Keywords
470	2010	Chemical Interaction Drug Discovery	drug, discovery, drug discovery, chemical, interaction
470	2010	Clinical Decision Support and Guidelines	clinical, decision, support, decision support, guideline
470	2010	Semantic Web and Gene Data	semantic, semantic web, web, data, gene
470	2010	Knowledge Graph and Relational Learning	graph, knowledge graph, knowledge, learning, relational
470	2010	Linked Open Data	linked, data, open data, open, linked open
267	2011	Healthcare Knowledge and Technology Translation	knowledge, health, technology, translation, knowledge translation
267	2011	Handheld Computer Use in Intensive Care	care, handheld, computer, hospital, intensive
267	2011	Student Reflective Learning and Practice	reflection, learning, student, practice, discussion
267	2011	Personal Digital Assistant Applications	personal digital, digital, digital assistant, assistant, personal
267	2011	—	—

Continued on next page

Community	Year	Topics	Top Keywords
140	2012	Smart Home and Ambient Assisted Living	smart home, home technology, home healthcare, home monitoring, home automation, ubiquitous healthcare, ambient assisted, ambient intelligence, assisted living, home environment
140	2012	POMDP and Markov Decision Planning	pomdp planning, planning pomdps, continuous pomdps, process pomdps, pomdps continuous, markov decision, approximate planning, online pomdp, pomdps, bayesian reinforcement
140	2012	Ambient Activity Recognition and Prediction	activity recognition, activity sensor, activity smart, home activity, smart home, activity prediction, detection ambient, smart environment, activity daily, learning ambient
140	2012	Social Robots for Child Autism Interaction	social robot, childrobot interaction, child autism, use robot, robot development, robot interaction, childrobot, interaction child, autistic child, robot

Continued on next page

Community	Year	Topics	Top Keywords
140	2012	Intelligent Robotic Wheelchair Navigation	smart wheelchair, intelligent wheelchair, wheelchair use, wheelchair control, wheelchair enable, wheelchair navigation, wheelchair user, powered wheelchair, wheelchair, robotic wheelchair
839	2013	OWL Query Rewriting and Answering	query, rewriting, answering, query answering, owl
839	2013	Clinical Guidelines and Patient Decision Support	clinical, guideline, patient, support, decision
839	2013	Chemical and Drug-Drug Interaction Discovery	drug, discovery, drug discovery, chemical, drugdrug
839	2013	Semantic Web and Data Integration	semantic, semantic web, web, data, integration
839	2013	Temporal Description Logic	logic, description logic, description, temporal, inf
125	2014	Respiratory and Lung Sound Classification	sound, respiratory, lung, respiratory sound, classification
125	2014	Fuzzy Decision Support for Diagnosis	decision, fuzzy, diagnosis, support, decision support
125	2014	Texture-Based Image Classification	texture, classification, texture classification, image, local
<i>Continued on next page</i>			

Community	Year	Topics	Top Keywords
125	2014	Glaucoma Progression and Visual Field Analysis	glaucoma, progression, visual field, visual, field
125	2014	Diabetic Retinopathy and Tear Biomarkers	diabetic, diabetic retinopathy, retinopathy, tear, biomarkers
581	2015	Texture-Based Image Classification	texture, classification, texture classification, image, local
581	2015	Fabric Defect Detection	defect, fabric, fabric defect, detection, defect detection
581	2015	—	—
581	2015	—	—
581	2015	—	—
819	2015	Chemical and Drug-Drug Interaction Discovery	drug, chemical, discovery, drug discovery, drugdrug interaction
819	2015	OWL Query Rewriting and Answering	query, answering, query answering, rewriting, owl
819	2015	Knowledge Graph Artifacts	knowledge, knowledge graph, graph, artifact, knowledge artifact
819	2015	Linked Open Data	linked, open data, data, linked open, open
819	2015	Biomedical Knowledge Graphs	graph, knowledge, knowledge graph, biomedical, biological
108	2015	Cross-Project Software Defect Prediction	defect prediction, defect, prediction, software defect, crossproject

Continued on next page

Community	Year	Topics	Top Keywords
108	2015	Software Effort Estimation	effort, estimation, effort estimation, software effort, software
108	2015	Fuzzy Decision Trees	tree, fuzzy, decision tree, decision, fuzzy decision
108	2015	Bug Triage and Developer Assignment	bug, bug triage, assignment, developer, triage
108	2015	Agile Software Release Planning	release, planning, release planning, software release, agile
290	2016	OWL Query Rewriting and Answering	query, answering, query answering, rewriting, owl
290	2016	Chemical and Drug-Drug Interaction Discovery	drug, drug discovery, discovery, chemical, drugdrug
290	2016	SPARQL Query Benchmarking on RDF	rdf, sparql, query, sparql query, benchmark
290	2016	Semantic Web for Biological Data Integration	semantic, web, semantic web, biological, integration
290	2016	Temporal Description Logic Dependencies	logic, description logic, description, temporal, dependency
40	2016	Software Effort Estimation	estimation, effort, effort estimation, software effort, software
40	2016	Fuzzy Decision Trees	tree, decision tree, fuzzy, decision, fuzzy decision

Continued on next page

Community	Year	Topics	Top Keywords
40	2016	Non-Functional Software Requirement Specification	requirement, software requirement, specification, nonfunctional requirement, nonfunctional
40	2016	Developer Social Network Profiles	social, developer, social network, software, profile
40	2016	Source Code Summarization and Completion	code, source code, summarization, completion, source
262	2016	Reflective Learning and Practice Change	learning, reflection, practice, change, statement
262	2016	Handheld Mobile Computers in Healthcare	healthcare, handheld, mobile, care, computer
262	2016	Healthcare Knowledge Translation and Technology	knowledge, health, knowledge translation, translation, technology
262	2016	—	—
262	2016	—	—
569	2018	OWL Query Rewriting and Answering	query, answering, query answering, rewriting, owl
569	2018	Chemical Drug-Drug Discovery	drug, drug discovery, chemical, discovery, drugdrug
569	2018	Biomedical Semantic Web	semantic, web, semantic web, biomedical, biological
569	2018	SPARQL Querying on RDF	rdf, sparql, query, database, sparql query
<i>Continued on next page</i>			

Community	Year	Topics	Top Keywords
569	2018	Knowledge Graph Learning Survey	graph, knowledge graph, knowledge, learning, survey
871	2020	Prostate Cancer Biopsy and Prostatectomy	prostate, prostate cancer, cancer, biopsy, prostatectomy
871	2020	Microplastics Pollution Identification	microplastics, microplastic, analysis, pollution, identification
871	2020	SERS Plasmonic Biosensors with Machine Learning	sers, detection, biosensors, plasmonic, machine
871	2020	Infrared Spectrum Baseline Correction	baseline, correction, baseline correction, infrared, spectrum
871	2020	Near-Infrared Fruit Quality and Ripening	quality, fruit, spectroscopy, ripening, infrared
424	2021	Molecular Vibrational Dynamics via Infrared Spectroscopy	vibrational, dynamic, molecular, infrared, spectroscopy
424	2021	Microplastics Environmental Pollution Analysis	microplastics, microplastic, pollution, analysis, environmental
424	2021	Protein Crystal Size Imaging	crystallization, crystal, image, protein, size
424	2021	SERS Plasmonic Biosensors	sers, biosensors, detection, plasmonic, sensor
424	2021	Nondestructive Fruit Ripening Quality	quality, fruit, spectroscopy, ripening, nondestructive

B.4 Thematic Data for Communities Interacting with Community

1160

Table B.4: Community 41: Thematic Evolution of Key Communities. Note: The column Year indicates the first year the respective community was detected in the cumulative network or the first year it was recorded as being involved in a convergence/divergence event with Community 41.

Community	Year	Topics	Top Keywords
238	2009	Protein Crystallization Propensity	crystallization, protein crystallization, protein, propensity, crystal
238	2009	Protein Secondary Structure Prediction	secondary, secondary structure, structure, prediction, protein structural
238	2009	Vaccine Design and Epitope Analysis	vaccine, design, epitope, virus, vaccine design
238	2009	RNA-Binding Residue Prediction	residue, binding, rnabinding, rna, prediction
238	2009	B-Cell Conformational Epitope Prediction	bcell, epitope, bcell epitope, conformational, epitope prediction
336	2010	Genome-Wide Disease Association Studies	genetic, association, disease, genomewide, association study
336	2010	Breast Cancer Machine Learning Analysis	breast, breast cancer, cancer, machine, machine learning
336	2010	Lung Cancer Prediction and Learning	lung, lung cancer, cancer, learning, prediction lung

Continued on next page

Community	Year	Topics	Top Keywords
336	2010	Radiation Oncology and Radiotherapy Treatment	radiotherapy, radiation, oncology, radiation oncology, treatment
336	2010	Alzheimer's Disease and Cognitive Brain Analysis	alzheimer, alzheimer disease, brain, disease, cognitive
863	2012	Hierarchical Clustering Algorithms	clustering, hierarchical, data, algorithm, cluster
863	2012	Somatic Mutation and Gene Networks in Cancer	cancer, somatic, mutation, gene, network
863	2012	Auction Game Theory and Agent Behavior	game, auction, agent, behavior, theory
863	2012	Patent Technology Development and Valuation Trends	patent, technology, development, trend, valuation
863	2012	Bayesian Network Structure Learning	bayesian network, bayesian, network, structure, learning
61	2013	Galaxy Transient Survey and Classification	survey, transient, galaxy, classification, learning
61	2013	Cancer Cell Protein and Molecular Conformation	cancer, cell, protein, molecular, conformational
61	2013	Urban Spatiotemporal Pattern Analysis	urban, spatiotemporal, pattern, data, spatial
61	2013	Density-Based Clustering	density, densitybased, clustering, densitybased clustering, peak
61	2013	Nanotechnology Patent Development and Valuation	patent, technology, development, valuation, nanotechnology

Continued on next page

Community	Year	Topics	Top Keywords
2519	2013	Pulsar Surveys	pulsar, pulsar survey, astronomy, astrophysics, machine learning
2519	2013	Astrophysical Discoveries	machine learning, data analysis, astronomical surveys, astrophysical discovery
2519	2013	—	—
2519	2013	—	—
2519	2013	—	—
1809	2014	Pulsar Candidate Classification	pulsar, pulsar candidate, candidate, network, learning
1809	2014	Radio Pulsar Survey	pulsar, survey, candidate, pulsar survey, radio
1809	2014	Synoptic Sky Survey	sky, survey, sky survey, synoptic, synoptic sky
1809	2014	Optical Gravitational Wave Detection	optical, gravitational wave, wave, gravitational, gravitationalwave
1809	2014	—	—
1958	2014	Topological Quantum Error Correction	quantum, code, error, topological, correction
1958	2014	Surface and Color Code Analysis	code, surface, surface code, color code, color
1958	2014	—	—
1958	2014	—	—

Continued on next page

Community	Year	Topics	Top Keywords
1958	2014	—	—
1134	2014	Sparse Function Learning and Modeling	learning, sparse, function, model, method
1134	2014	Auction Game Theory with Human Agents	game, agent, auction, human, theory
1134	2014	Web News Page Extraction and Wrappers	news, web, extraction, page, wrapper
1134	2014	AI Resource Survey for Disease and Policy	resource, intelligence, survey, disease, policy
1134	2014	—	—
1094	2015	Adaptive Phase Estimation and Bayesian Metrology	estimation, adaptive, phase, metrology, bayesian
1094	2015	Quantum Machine Learning	learning, machine, machine learning, quantum, learning quantum
1094	2015	Topological Quantum Code and Decoding	topological, code, topological quantum, topological code, decoder
1094	2015	Quantum Computing for Stock Data Analysis	stock, data, quantum, computing, quantum computing
1094	2015	Surface and Color Code Analysis	code, surface, surface code, color code, color
844	2015	Email Spam Filtering and Detection	spam, email, filtering, spam filtering, detection
<i>Continued on next page</i>			

Community	Year	Topics	Top Keywords
844	2015	Robust Support Vector Machines	robust, vector, support, support vector, vector machine
844	2015	Gene Expression and Cancer Network Analysis	gene, cancer, network, microarray, expression
844	2015	Crowdsourcing Task Learning	crowd, crowdsourcing, learning, learning crowd, task
844	2015	Noisy Label Learning	label, noise, label noise, noisy, noisy label
535	2017	Molecular Drug-Protein Interaction Prediction	molecular, drug, prediction, protein, interaction
535	2017	Collaborative Filtering Recommendation	recommendation, collaborative filtering, filtering, collaborative, recommender
535	2017	Attributed Network Embedding	network embedding, embedding, attributed network, attributed, network
535	2017	Adversarial Backdoor Attacks	attack, attack graph, backdoor, adversarial, adversarial attack
535	2017	Graph Contrastive Learning & Augmentation	contrastive learning, contrastive, graph contrastive, augmentation, learning
662	2019	ECG Arrhythmia Classification	ecg, arrhythmia, classification, electrocardiogram, cardiac
<i>Continued on next page</i>			

Community	Year	Topics	Top Keywords
662	2019	Tactile Object Sensing	tactile, sensor, tactile sensor, object, sensing
662	2019	Hand Gesture Recognition	gesture, gesture recognition, hand gesture, recognition, hand
662	2019	Surface Electromyography Signals	electromyography, surface, surface electromyography, electromyogram, electromyography signal
662	2019	mmWave FMCW Radar	radar, mmwave, fmcw, fmcw radar, mmwave radar

Appendix C

Community Network Visualizations and Node Mapping

C.1 Network Structure and Node Inventory for Community 15

Table C.1: Community 15: Node-Label Mapping Table (54 Unique Keywords). This table lists the node identifier and the corresponding keyword/theme. See Fig. 5.7 for the full network visualization.

Node	Representative Keyword
n24	Automated AI Planning and Plan Recognition
n25	Multi-Agent POMDP Planning and Policy
n26	Fall Detection in Healthcare
n27	Texas Hold'em Poker
n28	AI Abstraction Techniques
n29	Qualitative User Preference Learning
n30	Gait Event Detection
n31	Vocal Biomarkers

Continued on next page

Node	Representative Keyword
n32	Heuristic Search Planning for Sokoban
n33	Decision-Making under Uncertainty in Complex Systems
n34	Agent-Based Game Learning and Path Planning
n35	Intelligent Assistive
n36	Multiwinner Voting Manipulation and Rules
n37	Real-Time Heuristic Search
n38	Agent-Based Programming and Verification
n39	Chinese Chess Endgame Analysis
n40	Temporal Action Planning
n41	Heuristic Search Algorithms
n42	Nondeterministic Planning Problems
n43	No-Limit Poker Opponent Modeling
n44	Lifted Probabilistic Inference and Logic
n45	Intelligent Agent Design and Interaction
n46	Preference-Based Planning and Goal Setting
n47	Localization techniques
n48	Exploration Strategies in Reinforcement Learning
n49	Human Activity Analysis for Health Diagnostics
n50	Game Theory
n51	Monte Carlo Tree Search
n52	Temporal Difference Learning

Continued on next page

Node	Representative Keyword
n53	Robot and Multi-Robot Path Planning
n54	Automated Web Service Composition and Selection
n55	Real-Time and Bidirectional Heuristic Search
n56	Deep Multi-Agent Reinforcement Learning
n57	Imperfect Information Game Equilibrium Solving
n58	Parkinson's Disease (PD) Assessment
n59	Deep Learning for Human Activity Recognition
n60	Game-Theoretic Healthcare Monitoring
n61	StarCraft Real-Time Strategy
n62	Gait Analysis and Control
n63	Deep Neural Networks with Natural Gradient
n64	Game Evaluation and Tree Search
n65	Cognitive Machine Intelligence and Thinking
n66	Robot-Mediated Rehabilitation
n67	Reinforcement Learning in Game
n68	Deep Q-Learning and Q-Networks
n69	Imperfect Extensive-Form Game Equilibrium
n70	Computer Poker Strategy and Competition
n71	POMDP Point-Based Value Iteration
n72	Dementia Activity Monitoring with Home Technology
n73	Curiosity-Driven Exploration in Reinforcement Learning

Continued on next page

Node	Representative Keyword
n74	Gait Biometrics
n75	Alzheimer’s and Dementia in People
n76	Extensive-Form Game Solving with Regret
n77	Markov Probabilistic Logic Inference

C.2 Network Structure and Node Inventory for Community 5

Table C.2: Community 5: Node-Label Mapping Table (63 Unique Keywords). This table lists the node identifier and the corresponding keyword/theme. See Fig. 5.11 for the full network visualization.

Node	Representative Keyword
n24	Overall Water Splitting
n25	Alzheimer’s Disease Brain MRI Analysis
n26	Deep Malaria Parasite Detection
n27	Collaborative Filtering for Biomarker Discovery
n28	Diagnosis and Health Monitoring
n29	ECG Machine Diagnosis and Classification
n30	Astrocytoma Grading and Diagnosis
n31	Functional Brain Connectivity and Movement Decoding
n32	Data Mining and Knowledge Tools
n33	Multi-Agent Tutoring and Path Learning
n34	Supervised Continuous Attribute Discretization

Continued on next page

Node	Representative Keyword
n35	Dental Treatment Decision for Tooth
n36	PROAFTN Multicriteria Medical Classification
n37	Imbalanced Class Data Handling
n38	Blood Cell Image Segmentation
n39	Anomaly and Intrusion Attack Detection
n40	GNNs for Multi-Omics Cancer Data Analysis
n41	Natural Language Word Sense Disambiguation
n42	Protein-Drug Interaction and Association Prediction
n43	Privacy-Preserving Sensitive Data Hiding
n44	Anomaly Detection in Streaming Data
n45	Associative Classification
n46	Sequential Utility Pattern Mining
n47	Quantitative Structure-Activity Relationship Modeling
n48	High-Utility Itemset Mining
n49	Vaccine Immune Response Development
n50	Diabetic Retinopathy Tear Biomarkers
n51	Machine Learning for Heart Disease
n52	Uncertainty Quantification in Medical Imaging
n53	Neural Networks for Concrete and Alloy Analysis
n54	Fuzzy Multi-Objective Assignment Problems
n55	Neural Machine Diagnosis Classification

Continued on next page

Node	Representative Keyword
n56	Green Hydrogen Production
n57	Maritime Vessel Anomaly Detection
n58	Feature-Based Classification and Diagnosis Optimization
n59	Fuzzy Data-Driven Diagnosis Decision Support
n60	Particle Swarm Optimization
n61	Clinical Decision Support
n62	Association Rule Mining Classification
n63	Multilabel Classification and Learning
n64	Electronic Health Records
n65	Flow Cytometry Data Analysis
n66	ECG Arrhythmia and Heart Disease Analysis
n67	Fuzzy Programming for Assignment Problems
n68	Graph Neural Networks and Kernel Classification
n69	Functional Brain Connectivity in Aging and Disorders
n70	Association Rule Mining
n71	Vaccine Immune Response Development
n72	Log-Based Anomaly and Fault Detection
n73	Cross-Validation Error and Variance Estimation
n74	Performance Evaluation Metrics and Testing
n75	Acute Appendicitis and Abdominal Pain
n76	Medical Imaging

Continued on next page

Node	Representative Keyword
n77	Sequential Pattern Mining
n78	Proton Exchange Membrane Water Electrolysis
n79	Glaucoma Visual Field Progression
n80	Fuzzy Medical Information Diagnosis
n81	Intelligent Agent Decision Support
n82	Human-AI Collaboration
n83	Persistent Homology Topological Analysis
n84	Wind Power Energy Storage
n85	Bayesian Network Classifiers
n86	Fuzzy Medical Information Classification

C.3 Network Structure and Node Inventory for Community 41

Table C.3: Community 41: Node-Label Mapping Table (40 Unique Keywords). This table lists the node identifier and the corresponding keyword/theme. See Fig. 5.15 for the full network visualization.

Node	Representative Keyword
n24	Fuzzy Diagnosis Decision Support
n25	AI Cancer Chatbots
n26	Missing Value Imputation
n27	Texture-Based Image Classification
n28	Neural Network Preterm Birth Prediction

Continued on next page

Node	Representative Keyword
n29	IoT Smart Security Data Framework
n30	Home Rehabilitation
n31	Kernel Ensemble Lung Cancer Classification
n32	Literary Character and Speaker Attribution
n33	Ontology-Based Expert Fault Modeling
n34	Mobile Digital Health Monitoring
n35	BIQ Building Performance and Design
n36	Depression and Depressive Disorder Interventions
n37	Reflective Learning and Practice Statements
n38	Decision Support
n39	Cognitive Task Decision Support
n40	Medical Decision Support
n41	Glaucoma Diagnosis
n42	Holonic Multi-Agent Negotiation in Manufacturing
n43	Irrigation Reservoir Conflict Management
n44	Depression and Depressive Disorder
n45	Case-Based Reasoning (CBR)
n46	Fabric Defect Detection
n47	Tacit Health Knowledge Sharing
n48	Handheld Health Information Technology
n49	COVID-19 Mental Health Impact

Continued on next page

Node	Representative Keyword
n50	Glaucoma Diagnosis and Digital Decrease
n51	Digital Mental Health Tools
n52	Holonic Multi-Agent Manufacturing Control
n53	Medical Decision Support
n54	Protein Crystallization Imaging
n55	Smart Home Ambient Activity
n56	Healthcare Knowledge and Information Technology
n57	EEG-Based Disorder Detection
n58	AI-Driven Fuzzy Remediation Control
n59	Virtual Reality Mental Health Therapy
n60	Neural Network Mode Choice
n61	Data Analytics
n62	Glucose Anomaly Detection
n63	Ensemble CBR for Cancer Classification

C.4 Network Structure and Node Inventory for Community 1160

Table C.4: Community 1160: Node-Label Mapping Table (40 Unique Keywords). This table lists the node identifier and the corresponding keyword/theme. See Fig. 5.18 for the full network visualization.

Node	Representative Keyword
n24	ML-Based Structural Steel Damage

Continued on next page

Node	Representative Keyword
n25	Machine Learning for Data Classification
n26	Machinery Bearing Fault Diagnosis
n27	Policy and Bandit Reinforcement Learning
n28	Unsupervised Domain Adaptation
n29	Soft Sensor Modeling
n30	Adaptive Quantum Measurement and Metrology
n31	Unsupervised Person Reidentification
n32	Remaining Useful Life (RUL)
n33	Sparse Network Learning
n34	AI for Heart Disease Patients
n35	EMG Hand Gesture Recognition
n36	Data Transfer Learning
n37	Metabolic Pathway and Protein Prediction
n38	Distributed Consensus Optimization
n39	Domain Adaptive Object Detection
n40	Stochastic Nonconvex Optimization
n41	Quantum Machine Learning
n42	Adaptive Quantum Tomography
n43	Adversarial Domain Adaptation
n44	Quantum Machine Learning and Estimation
n45	Crosslingual Entity

Continued on next page

Node	Representative Keyword
n46	Quantum K-Means Clustering
n47	Style Domain Generalization
n48	Bayesian Graphical Models
n49	Information-Theoretic Generalization Bounds
n50	ECG and Heart Sound Arrhythmia
n51	Web Content Extraction
n52	ReLU Deep Neural Networks
n53	Quantum Reinforcement Learning Control

References

- Achiam, J., Adler, S., Agarwal, S., Ahmad, L., Akkaya, I., Aleman, F. L., . . . others (2023). Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*.
- Afifuddin, M., & Seo, W. (2024, February). Predictive modeling for technology convergence: A patent data-driven approach through technology topic networks. *Comput. Ind. Eng.*, 188(C). Retrieved from <https://doi.org/10.1016/j.cie.2024.109909> doi: 10.1016/j.cie.2024.109909
- Afifuddin, M., & Seo, W. (2025). Developing a predictive model for anticipating technology convergence: A transformer-based model and supervised learning approach. *PloS one*, 20(6), e0326417.
- Agnes, K., & Special, K. (2025, 07). Addressing bias in ai algorithms for health applications. *IAA Journal of Biological Sciences*, 13, 37-43. doi: 10.59298/IAAJB/2025/1313743
- Ahmed, M., Seraj, R., & Islam, S. M. S. (2020). The k-means algorithm: A comprehensive survey and performance evaluation. *Electronics*, 9(8), 1295.
- Aichholzer, G. (2009, 01). The delphi method: Eliciting experts' knowledge in technology foresight. In (p. 252-274). doi: 10.1057/9780230244276_13
- Al, U., Taşkın, Z., & Düzyol, G. (2012). Use of social network analysis in bibliometric researches. In *Information on e-motion. proceedings. bobcatss 2012, 20th international conference on information science, 23–25 january* (pp. 40–44).
- Albright, R. E. (2003). Roadmapping convergence. In *Managing nano-bio-info-cogno innovations* (pp. 23–31). Springer.
- Alcacer, J., & Gittelman, M. (2006). Patent citations as a measure of knowledge flows: The

- influence of examiner citations. *The review of economics and statistics*, 88(4), 774–779.
- Alkhayyat, A., Kumar, R., Al-Jawahry, H. M., Pareek, B. L., Kaur, J., & Jagtap, J. (2024). Exploring the role of ai in enhancing remote sensing technologies for climate change studies. In *2024 4th international conference on technological advancements in computational sciences (ictacs)* (pp. 1952–1957).
- Allison, J. R., & Lemley, M. A. (1998). Empirical evidence on the validity of litigated patents. *AIPLA QJ*, 26, 185.
- Andersen, P. (2022, 09). Constructing delphi statements for technology foresight. *Futures Foresight Science*, 5. doi: 10.1002/ffo2.144
- Andrey, S., Masoodi, J., Kwok, T., & Côté, A. (2023). An agenda for responsible technology policy in canada. *Canadian Public Administration*, 66(3), 439–446.
- Aquino, Y. S. J., Carter, S. M., Houssami, N., Braunack-Mayer, A., Win, K. T., Degeling, C., . . . Rogers, W. A. (2025). Practical, epistemic and normative implications of algorithmic bias in healthcare artificial intelligence: a qualitative study of multidisciplinary expert perspectives. *Journal of Medical Ethics*, 51(6), 420–428.
- Arumugam, V. R., Ng, B.-K., & Thambiratnam, K. (2023). A delphi study on technical and socio-economic perspectives of nanotechnology and ict industries relations. *Systems*, 11(4), 190.
- Attard-Frost, B., Brandusescu, A., & Lyons, K. (2024a). The governance of artificial intelligence in canada: Findings and opportunities from a review of 84 ai governance initiatives. *Government Information Quarterly*, 41(2), 101929.
- Attard-Frost, B., Brandusescu, A., & Lyons, K. (2024b). The governance of artificial intelligence in canada: Findings and opportunities from a review of 84 ai governance initiatives. *Government Information Quarterly*, 41(2), 101929.
- Bahoo, S., Cucculelli, M., Goga, X., & Mondolo, J. (2024). Artificial intelligence in finance: a comprehensive review through bibliometric and content analysis. *SN Business & Economics*, 4(2), 23.
- Bainbridge, W. S., & Roco, M. C. (2016). Science and technology convergence: with emphasis for nanotechnology-inspired convergence. *Journal of Nanoparticle Research*, 18(7), 211.
- Baktash, J. A., & Dawodi, M. (2023). Gpt-4: A review on advancements and opportunities in

- natural language processing. *arXiv preprint arXiv:2305.03195*.
- Baskerville, R. (2007). Educing theory from practice. In *Information systems action research: an applied view of emerging concepts and methods* (pp. 313–326). Springer.
- Bhatt, P. C., Hsu, Y.-C., Lai, K.-K., & Drave, V. A. (2025). From transactions to transformations: A bibliometric study on technology convergence in e-payments. *Applied System Innovation*, 8(4), 91.
- Bird, S., Klein, E., & Loper, E. (2009). *Natural language processing with python: analyzing text with the natural language toolkit*. ” O’Reilly Media, Inc.”.
- Bouterse, J., & Karstens, B. (2015). A diversity of divisions: Tracing the history of the demarcation between the sciences and the humanities. *Isis*, 106(2), 341–352.
- Brandao, P. R. (2025). The impact of artificial intelligence on modern society. *AI*, 6(8), 190.
- Bryan, V., Sood, S., & Johnston, C. (2025, June). *Analysis on artificial intelligence use by businesses in canada, second quarter of 2025* (Tech. Rep. No. Catalogue no. 11-621-M). Ottawa, Canada: Statistics Canada. Retrieved from <https://www150.statcan.gc.ca/n1/pub/11-621-m/11-621-m2025008-eng.htm> (Release date: June 16, 2025. Published by authority of the Minister responsible for Statistics Canada. © His Majesty the King in Right of Canada as represented by the Minister of Industry, 2025. Use governed by the Statistics Canada Open Licence Agreement.)
- Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.
- Cattaneo, M. C. (2014). Mazzucato m.(2013), the entrepreneurial state. debunking public vs. private sector myths. *Economia politica*, 31(1), 103–110.
- Chang, R. L., & Pavlidis, T. (2007). Fuzzy decision tree algorithms. *IEEE Transactions on systems, Man, and cybernetics*, 7(1), 28–35.
- Chen, C. (2011). Citespace ii: Detecting and visualizing emerging trends and transient patterns in scientific literature. *Journal of the American Society for Information Science and Technology*, 62(3), 537–548. (Analysis based on 600,000+ nanotechnology papers (1970–2008); focuses on co-citation networks for detecting bio-nanotechnology emergence) doi: 10.1002/asi.21448

- Chen, C. (2017). Science mapping: a systematic review of the literature. *Journal of data and information science*, 2(2).
- Coccia, M., & Wang, L. (2016). Evolution and convergence of the patterns of international scientific collaboration. *Proceedings of the National Academy of Sciences*, 113(8), 2057–2061.
- Cockburn, I. M., Henderson, R., Stern, S., et al. (2018). *The impact of artificial intelligence on innovation* (Vol. 24449). National bureau of economic research Cambridge, MA, USA.
- Cui, W., Tang, J., Zhang, Z., & Dai, X. (2023). A bibliometric analysis on innovation convergence. *Library Hi Tech*, 41(2), 333–354.
- Curran, C.-S., & Leker, J. (2011). Patent indicators for monitoring convergence—examples from nff and ict. *Technological forecasting and social change*, 78(2), 256–273.
- da Cruz, C. A. B., & Paixão, A. E. A. (2018). Bibliometric analysis of indicators system related to patents. *Razón y Palabra*, 22(103), 449–462.
- Dalkey, N., & Helmer, O. (1963). An experimental application of the delphi method to the use of experts. *Management science*, 9(3), 458–467.
- Da Silva, M., Flood, C. M., & Herder, M. (2022). Regulation of health-related artificial intelligence in medical devices: the canadian story. *UBCL Rev.*, 55, 635.
- Department of Finance Canada. (2017, March 22). *Investing in Canada: An innovative economy (Budget 2017)* (Tech. Rep.). Ottawa, Canada: Government of Canada. Retrieved from <https://www.budget.canada.ca/2017/docs/plan/budget-2017-en.pdf> (Accessed: 2025-08-26)
- Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2018). Bert: Bidirectional encoder representations from transformers. *arXiv preprint arXiv:1810.04805*, 15.
- Duong, T. Q. (2024). Quantum machine learning for 6g networks: Taxonomy, research challenges, and the road ahead. In *2024 rivf international conference on computing and communication technologies (rivf)* (pp. xxiv–xxiv).
- Ebadi, A., Auger, A., & Gauthier, Y. (2022). Detecting emerging technologies and their evolution using deep learning and weak signal analysis. *Journal of Informetrics*, 16(4), 101344.
- Fai, F., & von Tunzelmann, N. (2001). Industry-specific competencies and converging technological

- systems: evidence from patents. *Structural Change and Economic Dynamics*, 12(2), 141-170. Retrieved from <https://www.sciencedirect.com/science/article/pii/S0954349X00000357> doi: [https://doi.org/10.1016/S0954-349X\(00\)00035-7](https://doi.org/10.1016/S0954-349X(00)00035-7)
- Faluyi, S. E. (2025). Ai and job market: Analysing the potential impact of ai on employment, skills, and job displacement.
- Fer, E., McGrath, K. M., Guy, L., Hockenberry, A. J., & Kaçar, B. (2022). Early divergence of translation initiation and elongation factors. *Protein Science*, 31(9), e4393.
- for Advanced Research, C. I. (2017). Cifar pan-canadian artificial intelligence strategy.
- Furizal, F., Ma'arif, A., & Rifaldi, D. (2023, 09). Application of machine learning in healthcare and medicine: A review. *Journal of Robotics and Control (JRC)*, 4, 2023. doi: 10.18196/jrc.v4i5.19640
- Gaon, A., & Stedman, I. (2018). A call to action: Moving forward with the governance of artificial intelligence in canada. *Alta. L. Rev.*, 56, 1137.
- Gerdstri, N., & Daim, T. U. (2008). Generating intelligence on the research and development progress of emerging technologies using patent and publication information. In *2008 4th ieee international conference on management of innovation and technology* (pp. 1–6).
- Geum, Y.-J., Kim, C., Lee, S., & Kim, M.-S. (2012, 06). Technological convergence of it and bt: Evidence from patent analysis. *ETRI Journal*, 34. doi: 10.4218/etrij.12.1711.0010
- Giordano, V., Chiarello, F., Melluso, N., Fantoni, G., & Bonaccorsi, A. (2021). Text and dynamic network analysis for measuring technological convergence: A case study on defense patent data. *IEEE Transactions on Engineering Management*, 70(4), 1490–1503.
- Girvan, M., & Newman, M. E. (2002). Community structure in social and biological networks. *Proceedings of the national academy of sciences*, 99(12), 7821–7826.
- Goodchild, M. F. (2020). Foreword ii: Convergence and synthesis. In *Spatial synthesis: Computational social science and humanities* (pp. 7–9). Springer.
- Grootendorst, M. (2020). *Keybert: Minimal keyword extraction with bert*.
- Grootendorst, M. (2022). Bertopic: Neural topic modeling with a class-based tf-idf procedure. *arXiv preprint arXiv:2203.05794*.
- Grunevald, I., Kipper, L. M., Moraes, J. A. R., & Haupt, L. (2023). Scientific contributions on

- cleaner production through the use of patent information: A bibliometric analysis. *Renewable and Sustainable Energy Reviews*, 188, 113785.
- Guilarte, M. V. C. (2019). Divergent abduction model and its convergent interaction in knowledge production. In *New innovations in engineering education and naval engineering*. IntechOpen.
- Hachkevych, A. (2024). Tools for adapting ukraine's artificial intelligence ecosystem to meet european union standards. *L. & Innovative Soc'y*, 21.
- Hakim, Z., Ierasts, T., Hakim, I., D'Penha, A., Smith, K. P., & Caesar, M. C. (2020). Connecting data to insight: a pan-canadian study on ai in healthcare. *Healthcare quarterly (Toronto, Ont.)*, 23(1), 13–19.
- Hall, K. L., Stipelman, B. A., Vogel, A. L., & Stokols, D. (2017). Understanding cross-disciplinary team-based research. *The Oxford handbook of interdisciplinarity*, 338–356.
- Healy, J., & McInnes, L. (2024). Uniform manifold approximation and projection. *Nature Reviews Methods Primers*, 4(1), 82.
- Hey, T., Tansley, S., Tolle, K. M., et al. (2009). *The fourth paradigm: data-intensive scientific discovery* (Vol. 1). Microsoft research Redmond, WA.
- Hötte, K., Tarannum, T., Verendel, V., & Bennett, L. (2022). Exploring artificial intelligence as a general purpose technology with patent data—a systematic comparison of four classification approaches. *arXiv e-prints*, arXiv–2204.
- Illésová, S., Bezděk, T., Novák, V., Zelinka, I., Cacciatore, S., & Beseda, M. (2025). From classical to hybrid: A practical framework for quantum-enhanced learning. *arXiv preprint arXiv:2511.08205*.
- Ismail, H. A., Ali, M., & Ashour, S. (2025). 8 ai-powered personalized learning. *Artificial Intelligence and Responsible Management Education: Current Applications and Future Directions*.
- Ivanov, V. Y., Ungar, P. S., Ziker, J. P., Abdulmanova, S., Celis, G., Dixon, A., . . . others (2024). A convergence science approach to understanding the changing arctic. *Earth's Future*, 12(5), e2023EF004157.
- Jain, V., & Kulkarni, P. A. (2023). Integrating ai techniques for enhanced financial forecasting and budgeting strategies. *International Journal of Economics and Management Studies*, 10(09),

9–15.

- Johnson, J., Denning, P., Odlyzko, A., Walker, M., Delic, K., Yaffe, P., & Picton, P. (2025). Artificial intelligence: Foundational technologies of artificial intelligence. *Ubiquity*, 2025(July), 1–10.
- Jumper, J., Evans, R., Pritzel, A., Green, T., Figurnov, M., Ronneberger, O., ... others (2021). Highly accurate protein structure prediction with alphafold. *nature*, 596(7873), 583–589.
- Kagalwala, H., Radhakrishnan, G., Mohammed, I. A., Kothinti, R. R., & Kulkarni, N. (2025). Predictive analytics in supply chain management: The role of ai and machine learning in demand forecasting. *Advances in Consumer Research*, 2, 142–149.
- Kanama, D., & Kondo, A. (2007). The limitations of the technology roadmap and importance of new management tools in science-based innovation: the case of nanotechnology in japan. In *2007 ieee international conference on industrial engineering and engineering management* (pp. 2115–2119).
- Kanama, D., Kondo, A., & Yokoo, Y. (2008, 05). Development of technology foresight: Integration of technology roadmapping and the delphi method. *International Journal of Technology Intelligence and Planning - Int J Tech Intell Plann*, 4. doi: 10.1504/IJTIP.2008.018316
- Karvonen, M., & Kässi, T. (2013). Patent citations as a tool for analysing the early stages of convergence. *Technological Forecasting and Social Change*, 80(6), 1094–1107. Retrieved from <https://www.sciencedirect.com/science/article/pii/S0040162512001187> doi: <https://doi.org/10.1016/j.techfore.2012.05.006>
- Kaur, A., & Madaan, N. (2016). A study of hierarchical clustering. *Fuzzy Systems*, 8(5). Retrieved from <https://www.ciitresearch.org/dl/index.php/fs/article/view/FS052016005>.
- Kim, J., & Geum, Y. (2024). Identifying promising technologies considering technology convergence: A patent-based machine learning approach. *IEEE Transactions on Engineering Management*.
- Kim, J., & Lee, S. (2024). Technology opportunity analysis for creating innovative solutions: Applying semi-supervised topic modelling on patent data. In *2024 portland international conference on management of engineering and technology (picmet)* (pp. 1–9).
- Kocabas, S., Bilgic, E., Gorgy, A., & Harley, J. (2021). Deconstructing canada’s efforts to integrate

- artificial intelligence in medicine and medical education. *McGill Journal of Medicine*, 19(1).
- Kohonen, T. (1982). Self-organized formation of topologically correct feature maps. *Biological cybernetics*, 43(1), 59–69.
- Kolapo, A. A., & Adeyemo, S. (2025, 11). The convergence of ai innovation and public policy: Balancing competition, healthcare, and national growth.
- Koubaa, A. (2023). Gpt-4 vs. gpt-3.5: A concise showdown.
- Kumar, A. (2024). Redefining finance: The influence of artificial intelligence (ai) and machine learning (ml). *arXiv preprint arXiv:2410.15951*.
- Larnder, C. I., En, N. N., Vallerand, V., Holgado, O., Roy, N., Parent, S., . . . others (2024). *Éstate of the situation on the societal impacts of ai and digital technology-2024* (Unpublished doctoral dissertation). International Observatory on the Social Impacts of Intelligence . . .
- Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabasi, A.-L., Brewer, D., . . . others (2009). Social science. computational social science. *Science (New York, NY)*, 323(5915), 721–723.
- Lee, C., Hong, S., & Kim, J. (2021). Anticipating multi-technology convergence: A machine learning approach using patent information. *Scientometrics*, 126(3), 1867–1896.
- Lee, C., Kogler, D. F., & Lee, D. (2019). Capturing information on technology convergence, international collaboration, and knowledge flow from patent documents: A case of information and communication technology. *Information Processing & Management*, 56(4), 1576–1591.
- Lee, C., Park, G., & Kang, J. (2018). The impact of convergence between science and technology on innovation. *The Journal of Technology Transfer*, 43(2), 522–544.
- Lewis, J., Ritchie, J., Ormston, R., Morrell, G., et al. (2003). Generalising from qualitative research. *Qualitative research practice: A guide for social science students and researchers*, 2(347-362).
- Li, J. (2024). Understanding the interaction between the divergence of science and the convergence of technology based on polanyi's thoughts on science. *Foundations of Science*, 1–13.
- Liu, J. (2024). A survey of financial ai: Architectures, advances and open challenges. *arXiv preprint arXiv:2411.12747*.
- Liu, X., Hu, G., Du, Y., He, E., Luo, Y., Xu, C., . . . Zhu, J. (2024). Recent advances in end-to-end simultaneous speech translation. *arXiv preprint arXiv:2406.00497*.

- Liu, X., Li, L., & Liu, X. (2025). Generative artificial intelligence empowers administrative management in universities. *International Journal of Science and Research Archive*, 15(02), 1349–1353.
- Loganathan, E., Naveen, S., Yoganathan, A., Kalyanasundaram, P., Anitha, P., & Geetha, R. (2025). A comprehensive review of artificial intelligence approaches for climate change prediction using remote sensing data. In *2025 3rd international conference on sustainable computing and data communication systems (icscads)* (pp. 420–424).
- London, A. J. (2019). Artificial intelligence and black-box medical decisions: accuracy versus explainability. *Hastings Center Report*, 49(1), 15–21.
- MacQueen, J. (1967). Multivariate observations. In *Proceedings of the 5th Berkeley symposium on mathematical statistics and probability* (Vol. 1, pp. 281–297).
- Malzer, C., & Baum, M. (2019). Hdbscan (e): An alternative cluster extraction method for hdbscan. *CoRR*, abs/1911.02282.
- McInnes, L., Healy, J., Astels, S., et al. (2017). hdbscan: Hierarchical density based clustering. *J. Open Source Softw.*, 2(11), 205.
- McInnes, L., Healy, J., Saul, N., & Grossberger, L. (2018, 09). Umap: Uniform manifold approximation and projection. *Journal of Open Source Software*, 3, 861. doi: 10.21105/joss.00861
- Miller, G. (1995). Wordnet: a lexical database for english communications of the acm 38 (11) 3941. *Niemela, I.*
- Mohammed, A., & Kora, R. (2025). A comprehensive overview and analysis of large language models: Trends and challenges. *IEEE Access*.
- Monteiro, W. R., & Reynoso-Meza, G. (2022). A review of the convergence between explainable artificial intelligence and multi-objective optimization. *Authorea Preprints*.
- Moradi, M., Yan, K., Colwell, D., Samwald, M., & Asgari, R. (2025). A critical review of methods and challenges in large language models. *Computers, Materials & Continua*, 82(2).
- Moran, E. F., Lopez, M. C., Mourão, R., Brown, E., McCright, A. M., Walgren, J., ... others (2022). Advancing convergence research: Renewable energy solutions for off-grid communities. *Proceedings of the National Academy of Sciences*, 119(49), e2207754119.

- Mugabushaka, A.-M., Kyriakou, A., & Papazoglou, T. (2015). Bibliometric indicators of interdisciplinarity exploring new class of diversity measures. In *Issi*.
- Neto, A. C. A., Sander, J., Campello, R. J., & Nascimento, M. A. (2019). Efficient computation and visualization of multiple density-based clustering hierarchies. *IEEE Transactions on Knowledge and Data Engineering*, 33(8), 3075–3089.
- Newman, M. E. (2004). Fast algorithm for detecting community structure in networks. *Physical Review E—Statistical, Nonlinear, and Soft Matter Physics*, 69(6), 066133.
- Nordensvard, J., Zhou, Y., & Zhang, X. (2018, 05). Innovation core, innovation semi-periphery and technology transfer: The case of wind energy patents. *Energy Policy*, 120. doi: 10.1016/j.enpol.2018.04.048
- Oecd. (2016). *Oecd science, technology and innovation outlook*. OECD.
- Ouzounis, C. A., & Valencia, A. (2003). Early bioinformatics: the birth of a discipline—a personal view. *Bioinformatics*, 19(17), 2176–2190.
- Palacio-Niño, J.-O., & Berzal, F. (2024). Enhancing community detection in networks: A comparative analysis of local metrics and hierarchical algorithms. *arXiv preprint arXiv:2408.09072*.
- Paramaraj, A., et al. (2025). *Exploring the role of artificial intelligence in enhancing telemedicine accessibility, efficiency, and healthcare outcomes in rural canada* (Unpublished doctoral dissertation). University Canada West.
- Patil, A., Yadav, S., & Pandey, M. (2024). Exploring emerging trends in ai-driven technological advancements. *International Journal of Technology and Modeling*, 3(3), 138–151.
- Pedota, M., Grilli, L., & Piscitello, L. (2021). Technological paradigms and the power of convergence. *Industrial and Corporate Change*, 30(6), 1633–1654.
- Perez, C. (2002). *Technological revolutions and financial capital: The dynamics of bubbles and golden ages*. Edward Elgar Publishing.
- Porter, A., & Rafols, I. (2009). Is science becoming more interdisciplinary? measuring and mapping six research fields over time. *scientometrics*, 81(3), 719–745.
- Rahgoshay, M., & Salavatipour, M. R. (2021). Hierarchical clustering: New bounds and objective. *arXiv preprint arXiv:2111.06863*.

- Reimers, N., & Gurevych, I. (2019). Sentence-bert: Sentence embeddings using siamese bert-networks. *arXiv preprint arXiv:1908.10084*.
- Richey Jr, R. G., Chowdhury, S., Davis-Sramek, B., Giannakis, M., & Dwivedi, Y. K. (2023). *Artificial intelligence in logistics and supply chain management: A primer and roadmap for research* (Vol. 44) (No. 4). Wiley Online Library.
- Roco, M. (2016, 01). Convergence-divergence process. In (p. 79-93). doi: 10.1007/978-3-319-07052-0_11
- Roco, M., & Bainbridge, W. (2002). *Converging technologies for improving human performance: Nanotechnology, biotechnology, information technology and cognitive science*. doi: 10.1007/978-94-017-0359-8
- Röder, M., Both, A., & Hinneburg, A. (2015). Exploring the space of topic coherence measures. In *Proceedings of the eighth acm international conference on web search and data mining* (pp. 399–408).
- Rosenberg, N. (1963). Technological change in the machine tool industry, 1840–1910. *The journal of economic history*, 23(4), 414–443.
- Schwab, K. (2016). *The fourth industrial revolution*. World Economic Forum.
- Seo, W., & Afifuddin, M. (2024). Developing a supervised learning model for anticipating potential technology convergence between technology topics. *Technological Forecasting and Social Change*, 203, 123352.
- Sethi, I. (2025). Quantum machine learning techniques for high-performance pattern recognition. *International Journal of Research and Review in Applied Science, Humanities, and Technology*, 265–268.
- Shah, S. S. (2024). The impact of artificial intelligence on health outcomes: A review. *PREMIER JOURNAL OF SCIENCE : Eworkflow Ltd*, 1.
- Shi, J., Zhu, Q., Li, J., Liu, J., & Cheng, D. (2021). Hierarchical clustering based on local cores and sharing concept. In *2021 IEEE 45th annual computers, software, and applications conference (compsac)* (pp. 284–289).
- Skott, P. (1999). Economic divergence and institutional change: some observations on the convergence literature. *Journal of economic behavior & organization*, 39(3), 235–247.

- Song, J., Ebadi, A., Florea, A., Xi, P., Tremblay, S., & Wong, A. (2023). Covid-net uspro: an explainable few-shot deep prototypical network for covid-19 screening using point-of-care ultrasound. *Sensors*, 23(5), 2621.
- Soori, M., Arezoo, B., & Dastres, R. (2023). Artificial intelligence, machine learning and deep learning in advanced robotics, a review. *Cognitive Robotics*, 3, 54–70.
- Spiliopoulou, M., Ntoutsis, I., Theodoridis, Y., & Schult, R. (2006). The monic framework for cluster transition detection. In *Proc. of 5th hellenic data management symposium (hdms'2006), thessaloniki, hellas*.
- Sternfeld, A., Kucharavy, A., Percia David, D., Mermoud, A., Jang-Jaccard, J., & Monnet, N. (2025, 10). *Monitoring transformative technological convergence through llm-extracted semantic entity triple graphs*. doi: 10.48550/arXiv.2510.25370
- Suhana, S., & Karthiga, M. (2024). A survey on remote sensing-based climate change prediction using artificial intelligence techniques. In *2024 4th international conference on sustainable expert systems (icses)* (pp. 1324–1331).
- Sundstrom, S. M., Angeler, D. G., Bell, J., Hayes, M., Hodbod, J., Jalalzadeh-Fard, B., ... Allen, C. R. (2023). Panarchy theory for convergence. *Sustainability Science*, 18(4), 1667–1682.
- Tang, A., Tam, R., Cadrin-Chênevert, A., Guest, W., Chong, J., Barfett, J., ... others (2018). Canadian association of radiologists white paper on artificial intelligence in radiology. *Canadian Association of Radiologists Journal*, 69(2), 120–135.
- Taques, F. H. (2025). Mapping scientific knowledge on patents: A bibliometric analysis using patstat. *FinTech*, 4(3), 32.
- Team, G. R., Abeyruwan, S., Ainslie, J., Alayrac, J.-B., Arenas, M. G., Armstrong, T., ... others (2025). Gemini robotics: Bringing ai into the physical world. *arXiv preprint arXiv:2503.20020*.
- Thakur, A., Kaipa, K., Banerjee, A. G., Cappelleri, D. J., Krovi, V. N., & Gupta, S. K. (2025). Physical ai for powering the next revolution in robotics. *Journal of Computing and Information Science in Engineering*, 1–21.
- Tobi, H., & Kampen, J. K. (2018). Research design: the methodology for interdisciplinary research framework. *Quality & quantity*, 52(3), 1209–1225.

- Trappey, A. J., Trappey, C. V., Wu, C.-Y., & Lin, C.-W. (2012). A patent quality analysis for innovative technology and product development. *Advanced Engineering Informatics*, 26(1), 26-34. Retrieved from <https://www.sciencedirect.com/science/article/pii/S1474034611000486> (Network and Supply Chain System Integration for Mass Customization and Sustainable Behavior) doi: <https://doi.org/10.1016/j.aei.2011.06.005>
- Trump, B. D., Cummings, C. L., Loschin, N., Keisler, J. M., Wells, E. M., & Linkov, I. (2023). The worsening divergence of biotechnology: the importance of risk culture. *Frontiers in Bioengineering and Biotechnology*, 11, 1250298.
- Usmani, U. A., & Usmani, M. U. (2023). Ai-driven biomedical and health informatics: Harnessing artificial intelligence for improved healthcare solutions. In *2023 2nd international conference on futuristic technologies (incoft)* (pp. 1–7).
- Vaseashta, A. (2018). Roadmapping the future in defense and security: innovations in technology using multidisciplinary convergence. In *Advanced nanotechnologies for detection and defence against cbrn agents* (pp. 3–14). Springer.
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, 30.
- Vieira, P. A., Ouriques, H. R., & Pádua dos Santos, F. (2023). Trajetórias divergentes: a américa latina e o leste asiático na economia-mundo capitalista. *Colombia Internacional*(113), 23–59.
- Wan, T. T. (2023). Convergence of artificial intelligence research in healthcare: trends and approaches. *Journal of Integrated Design and Process Science*, 26(3-4), 291–305.
- Wang, J., & Lee, J.-J. (2023). Predicting and analyzing technology convergence for exploring technological opportunities in the smart health industry. *Computers & Industrial Engineering*, 182, 109352.
- Wang, J., & Su, X. (2011). An improved k-means clustering algorithm. In *2011 ieee 3rd international conference on communication software and networks* (pp. 44–46).
- Williams, R. (2008). Applying practice to theory. *ACM SIGACT News*, 39(4), 37–52.
- Zade, N., Gawande, M., Verma, P., & Gundewar, S. (2024). The future of driving: A review on the combination of artificial intelligence and autonomous vehicles. In *2024 2nd dmiher international conference on artificial intelligence in healthcare, education and industry (idicaiei)*

(pp. 1–6).

- Zhang, J., Li, S., & Li, M. (2010). A comparison of self-organizing feature map clustering with twinspan and fuzzy c-means clustering in the analysis of woodland communities in the guan-cen mts, china. *Community Ecology*, 11(1), 120–126.
- Zhang, Q. (2024). Harnessing artificial intelligence for personalized learning pathways: A framework for adaptive education management systems. *Applied and Computational Engineering*, 82(1), 167–172.
- Zhou, Y., Dong, F., Kong, D., & Liu, Y. (2019). Unfolding the convergence process of scientific knowledge for the early identification of emerging technologies. *Technological Forecasting and Social Change*, 144, 205-220. Retrieved from <https://www.sciencedirect.com/science/article/pii/S0040162518310096> doi: <https://doi.org/10.1016/j.techfore.2019.03.014>
- Zucker, L. G., & Darby, M. R. (2009). Star scientists, innovation and regional and national immigration. In *Entrepreneurship and openness*. Edward Elgar Publishing.
- Ávila Robinson, A., & Miyazaki, K. (2013, 07). Dynamics of scientific knowledge bases as proxies for discerning technological emergence — the case of mems/nems technologies. *Technological Forecasting and Social Change*, 80, 1071–1084. doi: 10.1016/j.techfore.2012.07.012