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Technological Convergence of AI Across the Industrial Sectors

Dae-hyun Jeong [a], O Young Kown [b], Eunjin Hwang [c,*]

[a] Gangwon Institute, 880, Baksa-ro, Seo-myeon, Chuncheon-si, Gangwon State, 24461, Republic of Korea
[b] Seongnam Research Institute, 46 Daleanearo, Sujung-gu, Seongnam-si, Gyeonggi-do, 13449, Republic of Korea
[c] Jeju National University, 102 Jejudaehak-ro, Jeju-si, Special Self-Governing Province, 63243, Republic of Korea
Corresponding author: [*]ejhwang@jejunu.ac.kr

***Abstract*—The AI market has been experiencing significant growth recently and is projected to thrive. Yet, there is still a lack of comprehensive studies integrating diverse industries and technologies in AI. Furthermore, AI-related patent analysis often examines AI technologies without considering their convergence with other sectors. Therefore, to fill this gap, this study aims to explore the technological convergence of AI using a network analysis approach with patent data in finance & management, healthcare, semiconductors, games, biotechnology, and transport. This study used an IPC-based convergence network methodology to define critical industrial areas and influential technologies with the four-digit IPC codes for the AI patent group from 2000 to 2019. Moreover, this study conducted a centrality analysis using Net-Miner software to identify hubs and connected nodes and analyze the comprehensive convergence status related to AI. According to the results, we defined hub nodes based on the degree and centralities and analyzed the centrality of six sectors in the AI convergence network. In addition, the technology classification of solid ties is analyzed based on IPC network analysis. Finally, this study attempts to deliver theoretical and empirical contributions to technological convergence, providing a comprehensive framework for understanding how different technologies can converge in AI with three categories: 1) learning and reasoning, 2) natural language processing, and 3) computer vision. This study suggests that companies operating within the industrial AI space should reflect the evolution of technology as revealed in the mainstream trends of sector-specific AI integration.**

***Keywords*—Artificial intelligence; technological convergence; network analysis; centrality analysis.**

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I. Introduction

Artificial intelligence (AI) has garnered significant interest across the ICT industry, its products, and various other fields. For example, regarding health care, AI is already used to advise patients about interpreting CT scans based on systematic monitoring [1], [2]. In addition, AI is recognized as a megatrend for electrified and autonomous driving and shared mobility within the automotive industry and robo-advisory platforms based on AI in the finance industry [3], [4]. Likewise, the impact of AI is reshaping numerous industries, with its application expanding steadily across different sectors. Artificial intelligence has not only driven technological advancements and sparked novel innovations but is also designed to comprehend a general-purpose technology (GPT), becoming a broadly applicable technology. [5]. Prior research has established that AI influences technological innovation by enhancing the generation and transfer of knowledge, boosting the ability to assimilate new information, and catalyzing more significant investments in research and development. This elucidates the substantial link between AI-driven technological innovation and its beneficial effects, which vary across industries with different levels of technological sophistication, from high-tech to low-tech sectors. [5]. In addition, relevant research has empirically investigated AI, revealing that it is a vital factor in enhancing the innovative output of manufacturing firms. [6], [7]. Moreover, AI impacts General-Purpose Technology (GPT), increasing productivity and associated innovations [8]. AI has the potential to catalyze groundbreaking changes and bring about a shift in the prevailing paradigm by integrating different sectors. Consequently, there is a societal imperative to advance AI with an awareness of its repercussions across diverse industries. [9].

Based on the literature and societal trends, we can confirm that AI, which impacts various industries, has become imperative to the development of our society. However, previous studies in AI have generally focused on examining a particular industry sector [1]-[4], and those studies typically have yet to concentrate on gathering insights from various industries. In contrast, certain studies examining the industrial influence of AI have often centered on assessing the economic effects across different sectors [3], [4], [10], those have not explored the comparison of technological aspects from the standpoint of technological convergence across different industries [11].

The concept of technological convergence is viewed as a catalyst for technological advancements, and there has been a rise in interdisciplinary research focusing on amalgamating diverse technologies [12]. Technological convergence describes the phenomenon where previously distinct industries overlap and utilize a shared foundation of knowledge and technology [13]. The exchange of technological traits has hastened the breakdown of traditional boundaries between various industries [14]. The development of technological convergence results in the blending of each sector [15], [16], and industry convergence could take place when there is a unification of different technologies [16].

Despite many researchers having investigated the concept of convergence from diverse perspectives, earlier research on AI has yet to thoroughly examine the comprehensive approach considering both the diverse industries and individual technology [17]. Accordingly, this study explores the technological convergence of AI, reflecting various industries and technologies by conducting the network analysis approach with patents, which are reliable data sources for technological intelligence. This work can provide invaluable insight into the potential relationships of AI technologies. Network analysis discovers hidden connections and understands the structure of complex relationships within ties [18].

II. Materials and Method

A. Technological Convergence

The idea of convergence gained prominence in shedding light on how industries were merging before the surge in information technology during the 1980s. Convergence refers to two or more distinct elements coming together toward a common point or the fusion of separate technologies, devices, or sectors into a cohesive entity. [19]. Prior research has utilized the term 'convergence' to describe the phenomenon where the lines between two or more sectors become indistinct, a process also referred to as industry convergence or fusion [20]. Although the terms 'convergence' and 'fusion' are often synonyms [19], we contend there is a distinct difference between them. Convergence involves distinct items coming together toward a particular point [21]. However, fusion pertains to the diminishing distinctions between entities within the same space. Despite our equal interest in both phenomena, we choose to employ the term 'convergence' for the sake of greater precision.

The term convergence is primarily utilized in technology, with an increasing number of people and organizations reaping the advantages of merging information technology (IT) with traditional technologies. Since technologies have developed, technological convergence was introduced as a term to describe the progress in the machinery device sector in the United States in the late 1980s. [22]. Technological convergence combines different technological systems, such as voice and video, that can share and interact synergistically to evolve toward performing similar tasks [23]. Convergence is a process characterized by an ongoing imbalance between a primary technology and its complementary technology, which continually recalibrates the ideal equilibrium of functions between both technologies. [24].

Technological convergence has resurfaced in recent years as a concept to characterize the evident fusion of data communication, information technology, media, and entertainment into a colossal industry encompassing information and communication technology (ICT) and multimedia [25]. Accordingly, there has been a resurgence of attention on the concept of convergence within business academia [26], igniting what is currently seen as a burgeoning and reflective debate on the topic. The term is also applied across various academic fields, including mathematics and natural and social sciences like computer science and economics. In the management literature, the term 'convergence' appears in various scenarios [27]. While some scholars refer to it as incorporating diverse new features into existing core products, others focus on technological convergence, which refers to applying technology from one industrial domain into a completely new one [28].

Cross-disciplinary citations will set in motion a scientific convergence that is likely to evolve into more collaborative research efforts. As the gap between fundamental scientific fields narrows significantly, this should pave the way for advancements in applied science and technological development, ultimately culminating in technological convergence. Subsequently, novel combinations of products and markets will surface, resulting in the convergence of markets. As companies start to amalgamate, this sequence of events will culminate in the final phase of industry convergence [29]. Despite recognizing that this process is considerably simplified and idealized, some researchers acknowledge that industry convergence happens only when both technologies and markets merge.

B. Social Network Analysis and Patent Network Analysis

Social network analysis (SNA), known for its efficacy in examining and comprehending diverse aspects of networks, is a potent instrument for depicting a comprehensive view of network architecture and its elements [30]. Moreover, SNA highlights the connections of any given node within a network, with the nodes representing the participants (e.g., an individual, a department, or an institution, …), and the relationship is described as arrows between knots. Understanding the network structure, such as frequency, type of relationship, and strength of the interaction, is essential because its ability to uncover numerous details about the data is often overlooked [31]. In this respect, numerous researchers have investigated various local and global metrics to discover the potential opportunities within the network.

Additionally, patents are recognized as a vital form of intellectual property, safeguarding the entitlements of organizations and innovators. Patents are typically acknowledged as reliable and current repositories of technological expertise and inventive concepts. Moreover, patent information can often generate the predictive path of technology's evolution and its life cycle. Consequently, many researchers have utilized patent repositories of information to forecast technological convergence and trends across sectors [32]. Given that patent network analysis (PNA) is a well-known application of SNA, many scholars have conducted PNA to examine technological trends [32], [33]. Typically, patent data is evaluated based on its relevance to PNA, focusing on elements like citation details, International Patent Classification (IPC) codes, and patent identifiers. These networks formed by patents enable researchers to analyze the connections between nodes and forecast dominant technology areas. Additionally, numerous companies employ patent documentation as a strategic tool for recording technology strategies, encompassing mergers and acquisitions, technology transfers, and technology procurement.

C. Centrality Analysis

Centrality analysis identifies the most influential node or entity within a network, characterized by the most robust node that maintains numerous links to a central hub [34]. Such nodes govern the distribution and management of knowledge across the network. Several metrics exist for gauging the centrality within a network, and the choice depends on the particular requirements. Key indicators commonly considered include degree centrality, closeness centrality, and betweenness centrality [35].

Degree centrality measures a particular node or entity's connections with other nodes. It represents the most straightforward and primary metric for assessing a node's centrality within a network. This count, known as local centrality, quantifies a specific node's or entity's level of connectedness. A node with a substantial number of immediate links to others is deemed more central regarding the degree centrality index [36]. However, a central node isn't necessarily located at the physical center of the network. Closeness centrality reflects the proximity of nodes to all other nodes in the network, whether they're connected directly or through intermediary points. Consequently, a node's centrality is proportional to its proximity to all other nodes—the closer it is, the more central the node. This proximity allows the node to acquire and disseminate information across the network more efficiently. Moreover, the effectiveness of information transmission is also greatly influenced by its closeness to the entire network [37]. Furthermore, betweenness centrality evaluates how often a particular node lies along the shortest paths connecting other nodes, essentially serving as the quickest conduit for information flow and acting as a bridge for other nodes. Nodes exhibiting substantial betweenness centrality are seen as pivotal intermediaries (comparable to gatekeepers) within the network. Nodes with elevated levels of betweenness centrality are crucial for linking various subgroups and individual nodes throughout the network due to their influential position and function.

D. Data and Methodology

1) Data: Numerous attempts have been made to create a distinct category of patents within the field of artificial intelligence. Prior studies have divided AI into three domains: analytics involving large datasets, image processing, and linguistics. Similarly, to delineate our study's parameters, AI software technologies are categorized into three distinct classifications.: (1) learning and reasoning (L&A), (2) natural language processing (NLP), and (3) computer vision (CV). According to previous studies, International Patent Classification (IPC) codes, a hierarchical arrangement system, were employed to select and categorize AI-related technologies. [38]. Comprehensively, we collected patents from the three identified groups associated with the IPC system. The allocation of IPC codes to the respective groups of AI patents in our investigation was based on the classifications established by the 2018 Korean Intellectual Property Office. Table 1 displays this research's AI tech classification and IPC codes. For the descriptions of the IPC code, we referred to the documentation provided by the World Intellectual Property Organization [39].

TABLE I
CATEGORY OF AI TECHNOLOGY

AI patent group	**IPC code**	**Description**
L&A	G06N-003/08	Learning methods: Computer systems (biological models)
	G06N-005/04	Inference methods or devices: Computer systems (knowledge-based models)
	G06F-019/24	Digital computing or data processing equipment or methods, specially adapted for specific applications, For machine learning, data mining or biostatistics, e.g. pattern finding, knowledge discovery, rule extraction, correlation, clustering or classification
	G06K-009/62	Methods or arrangements for reading or recognizing printed or written characters or for recognizing patterns; Methods or arrangements for recognition using electronic means
	G06N-003/02	Neural network models
NLP	G06F-017/20	Natural language data (speech analysis or synthesis)
	G06F-017/21	Text processing
	G06F-017/27	Automatic analysis, e.g. parsing, orthography correction
	G06F-017/28	natural language processing or translating
	G10L-015/	Recognition of Speech
	G10L-017/	Identification or verification of Speaker
	G10L-013/	Speech synthesis; Text to speech systems
CV	G06F-021/32	User authentication (biometric data) e.g. fingerprints, iris scans or voiceprints
	G06K-009/00	Recognizing patterns using several methods for reading or recognizing printed or written characters e.g. fingerprints
	G06T-007/50	Image analysis; Depth or shape recovery

AI-related patents were collected for this study and registered in the Science-On database from KISTI. We collected AI-related patents based on IPC codes, and their publication date was from 2000 to 2019. The total amount of patents was 84,768. Moreover, IPC codes were used to analyze case studies as they covered information on technological fields. Specifically, for this study, we employed the subclass levels of the IPC codes, matching a four-digit IPC classification. Earlier, such four-digit IPC codes have been employed to identify sustainable technologies and to project key technologies using social network analysis techniques.

2) Methodology: The patent information was collected from the Science-On database. After collecting AI patents, data was used to preprocess and extract the IPC codes. These IPC codes were then tailored to fit our specific research questions. Following this preprocessing, the IPC codes were applied to form a connection matrix representing each year's patents. Subsequently, using these connection matrices, the annual technological networks were established using the network visualization software Net-Miner. Additionally, a centrality analysis was performed using the network data. Employing these processed IPC codes, we constructed annual connection matrices for the patents, which then served as a foundational element for developing the technology network of each year through network analysis methods utilizing the Net-Miner.

III. Results and Discussion

For this research, hub nodes were categorized as those ranking within the highest 10 based on degree and betweenness centralities. It was clear that most hub nodes were associated with AI or computing technologies, such as pattern detection and data clustering in social networks. Specifically, G06K-009 of the IPC code, which is associated with pattern recognition, consistently achieved the top ranking in degree and betweenness centrality, placing it at the core of the entire network of AI convergence.

TABLE II
Top10 rank of the IPC codes in AI convergence network

	Rank	IPC	Value	Description
Degree Centrality	1	G06K-009	0.878	Recognizing patterns of written characters or printed
	2	G06T-007	0.480	Image analysis
	3	G06F-017	0.378	Data processing methods
	4	G06F-003	0.328	Input or output plans for transferring data
	5	H04N-005	0.313	Details of television systems
	6	H04N-007	0.293	Television systems
	7	A61B-005	0.274	Measurement for diagnosis
	8	G06F-019	0.267	Data processing methods
	9	G10L-015	0.243	Speech recognition
	10	G06Q-010	0.202	Business management
Betweenness Centrality	1	G06K-009	0.526	Same above
	2	G06T-007	0.085	Same above
	3	G06F-017	0.052	Same above
	4	G06F-019	0.034	Same above
	5	G06F-003	0.032	Same above
	6	G10L-015	0.030	Same above
	7	H04N-005	0.022	Same above
	8	G06N-003	0.021	Same above
	9	H04N-007	0.021	Same above
	10	A61B-005	0.019	Same above

In addition, we analyzed the centrality of six sectors (biotechnology, finance management, medical, semiconductor, game, and transport) in the AI convergence connection structure. Table 3 displays the hub's results across sectors. Technology-related measuring test processes (G01N-033) ranked high in the biotechnology sector. Regarding the finance and management sectors, technologies related to business and management systems (G06Q-010, G06Q-050) and commerce (G06Q-030) ranked high. Video game technology (A63F-013) ranked relatively high in the game sectors.

TABLE III
Network centrality analysis on the hub by sectors

Sector	Hub	Degree Centrality		Betweenness Centrality	
		Rank	Value	Rank	Value
Biotechnology	C12Q-001	111	0.053	46	0.002
	G01N-033	33	0.136	15	0.008
Finance/ Management	G06Q-010	10	0.202	13	0.009
	G06Q-020	54	0.102	48	0.002
	G06Q-030	16	0.172	25	0.004
	G06Q-040	76	0.075	106	0.000
	G06Q-050	11	0.187	21	0.006
Game	A63B-024	78	0.074	63	0.002
	A63B-069	189	0.033	169	0.000
	A63B-071	102	0.056	78	0.001
	A63F-013	68	0.083	73	0.001
Medical	A61B-003	61	0.089	82	0.001
	A61B-005	7	0.274	10	0.019

Sector	Hub	Degree Centrality		Betweenness Centrality	
		Rank	Value	Rank	Value
	A61B-006	67	0.083	69	0.001
	A61B-008	113	0.052	155	0.000
	A61B-017	141	0.045	177	0.000
Semiconductor	H01L-021	179	0.036	114	0.000
	H01L-023	286	0.021	237	0.000
	H01L-027	136	0.047	103	0.001
Transport	B60N-002	256	0.024	219	0.000
	B60Q-001	70	0.080	97	0.001
	B60R-001	51	0.107	55	0.002
	B60R-011	85	0.068	92	0.001
	B60R-016	88	0.063	182	0.000
	B60R-021	160	0.040	264	0.000
	B60R-025	96	0.060	181	0.000
	B60W-010	149	0.044	164	0.000
	B60W-030	83	0.070	94	0.001
	B60W-040	79	0.072	102	0.001
	B60W-050	74	0.077	138	0.000
	B64C-039	190	0.033	241	0.000
	B64D-047	185	0.034	204	0.000

We conducted a network analysis based on the International Patent Classification (IPC) codes and found the top 10 strong-ties of robust connections. These significant interconnections are detailed in Table 4. As defined by the World Intellectual Property Organization (WIPO) descriptions for IPC, these strong ties are highly related to AI technologies, such as identifying patterns in data, data processing techniques, and converting spoken language into text. To ascertain the intensity of these strong ties within specific industrial sectors and contrast them with ties in other sectors, we explored the prevalence of common or unique technologies across different industries.

TABLE IV
TIES IN IPC NETWORK

Sector		Hub	Ties
Finance & Mgmt.	Commerce	G06Q-030	G06F-017, G06K-009, H04N-005, G06F-003, H04N-007, G06N-005, G10L-015, H04N-021
	Business Management system	G06Q-010	G06F-017, G06K-009, G06F-003, H04N-007, H04N-005, G06N-005, H04N-021, G10L-015
		G06Q-050	G06F-017, G06K-009, G06F-019, G06N-005, H04L-029, G10L-015, G06T-007, G06F-003, G06F-021
	Insurance and tax	G06Q-020	G06K-009, G06F-017, H04N-005, H04N-007, G06F-021, H04N-021, A63F-013, A61F-009
	Payment	G06Q-040	G06K-009, G06F-017, H04N-021, H04N-005, H04N-007, A63F-013, A61F-009, G06F-021
Medical	Diagnosis	A61B-005	G06K-009, G06T-007, G06F-019, G06F-003, G06F-017, G01R-033, G06T-003, H04N-005, G06T-011
		A61B-006	G06K-009, G06T-007, G06T-011, G06T-005, G06F-019, G01R-033, G06T-017, G06F-017, G06G-007
		A61B-008	G06K-009, G06T-007, G06F-019, G01R-033, G06T-017, G06G-007, G06T-011, G06F-017, G01S-007
	Examination	A61B-003	G06K-009, G06F-003, G06T-007, H04N-005, G02B-027, H04N-007, G09G-005, G06F-019, G06F-001, G08B-021
	Surgical instrument	A61B-017	G06K-009, G06T-007, A61F-002, G06T-019, A61B-008, G06F-019
Semi-conductor	Manufacturing process	H01L-021	G06K-009, G06T-007, G01N-021, H01J-037, H01L-023, G06F-019, G01R-031, G01B-011, G21K-005, G05B-019, G01N-023
	Device	H01L-027	G06K-009, H01L-031, A61B-005, G06F-003, H01L-029, H04N-005, H04N-009, G01N-033, G02B-005, H03K-019
		H01L-023	G06K-009, G06T-007, H01L-025, H05K-001, G06K-019, H04R-025, G01N-001, H01L-029
Game	Industrial video game	A63F-013	G06K-009, G06F-017, H04N-005, H04N-021, H04N-007, G06Q-030, G06Q-020, A61F-009, G06Q-040, G06Q-010
	Sports/exercise	A63B-071	G06K-009, G06F-019, G09B-019, G06F-017,

Sector		Hub	Ties
			G06Q-050, G06F-003, H04L-029, H04W-004
		A63B-069	G06K-009, G09B-019, G06T-007, G06F-019, A63B-053, G06Q-010
		A63B-024	G06K-009, G06F-019, G09B-019, G06N-005, G01P-015, G06F-003, H04L-029
Biotechnology	Analyzing materials	G01N-033	G06K-009, G06F-019, G06T-007, G01N-015, G01N-021, A61B-005, G06F-017, G06G-007, C40B-030, C12M-001
	Measuring Test process	C12Q-001	G01B-021, G02B-021, G01J-001, G06F-019, G06T-005, G07B-015, G06K-009, B60R-025, B66B-001, A45D-044
Transport	Vehicle control	B60W-030	G06K-009, G08G-001, G05D-001, G06T-007, H04N-007
		B60W-050	G06K-009, G06F-017, G06T-007, G10L-015, G06F-003, H04N-005, G06F-021, H04L-029, H04N-007, G06N-005, G10L-021
		B60W-040	G08G-001, G05D-001, G06K-009, G01C-021, G07C-009, G05D-023, H04W-004, H04W-076, H04W-048, G08B-025, G06F-003, H04W-036
		B60W-010	G06K-009, G06T-007, H04N-013, G01C-021
		B60R-011	G06K-009, G06T-007, H04N-007, H04N-005, H04N-013, G08G-001, G05D-001, B62D-006, B65B-001, A01D-043
		B60R-016	G01C-021, G06F-017, G06K-009, G08G-001, G07C-009, G05D-001, G05D-023
		B60R-021	G06K-009, G06T-007, G08G-001, H04N-007, G05D-001
		B60R-025	G07C-009, G06F-003, G05D-001, G01C-021, G05D-023, G08G-001, H04W-004, H04W-076, G08B-013, H04N-021, H04W-048, G08B-025, H04W-036, G06K-009, G06F-021
	Vehicle device	B60R-001	G06K-009, H04N-007, G06T-007, G08G-001, H04N-005, G01C-021, H04N-013
		B60Q-001	G06K-009, G06F-017, G06T-007, G10L-015, G06F-003, H04N-005, G06F-021, H04L-029, H04N-007, G06N-005, G10L-021
	Seat management of vehicle	B60N-002	G06K-009, G10L-015, G10L-021, G06F-003, H04N-007, G10L-025
		B60R-025	G07C-009, G06F-003, G05D-001, G01C-021, G05D-023, G08G-001, H04W-004, H04W-076, G08B-013, H04N-021, H04W-048, G08B-025, H04W-036, G06K-009, G06F-021
	Aircraft	B64C-039	G06K-009, B64C-039, G05D-001, B64D-047, G08G-005, G06T-007, H04N-005, H04N-007, G08G-001, G01S-013, B64D-045, H02S-050
		B64D-047	G06K-009, G06T-007, B64C-039, H04N-005, H04N-007, G08G-005

Consequently, Fig.1 summarizes the findings of this research, presenting the key technologies and their interconnections within each industrial sector based on the hub and tie data obtained from the network analyses. As depicted in Fig. 1, the hubs represent the technologies with significant influence, while the ties highlight the closely interrelated technologies in each industry.

IV. Conclusion

This empirical study aims to gain insights into technological convergence, focusing on artificial intelligence (AI). In pursuit of this goal, the study employs network centrality analysis to explore how various industrial sectors intersect through AI. Consequently, it highlights six key sectors that notably demonstrate the degree of technological convergence, offering a measure to assess and scrutinize the integration of technologies. Theoretical contributions to technological convergence are summarized as follows.

This study provides a comprehensive approach to defining features of technological convergence. It recommends an organized viewpoint on technological convergence based on different sectors and several technological categories. Methodologically, this study contributes in specific ways. It innovatively utilizes network analysis techniques on structured data from patent documentation. This analytical approach serves as a tangible metric to discern patterns within technological convergence, providing a clear and quantifiable means of understanding these complex interactions.

The research has significant practical relevance for AI technology and its intersecting sectors. Viewing AI from strategic business planning, it emerges as a catalyst for forging a fresh paradigm through disruptive innovation. As suggested by this study, companies operating within the industrial AI space should reflect the evolution of technology as revealed in the mainstream trends of sector-specific AI integration.

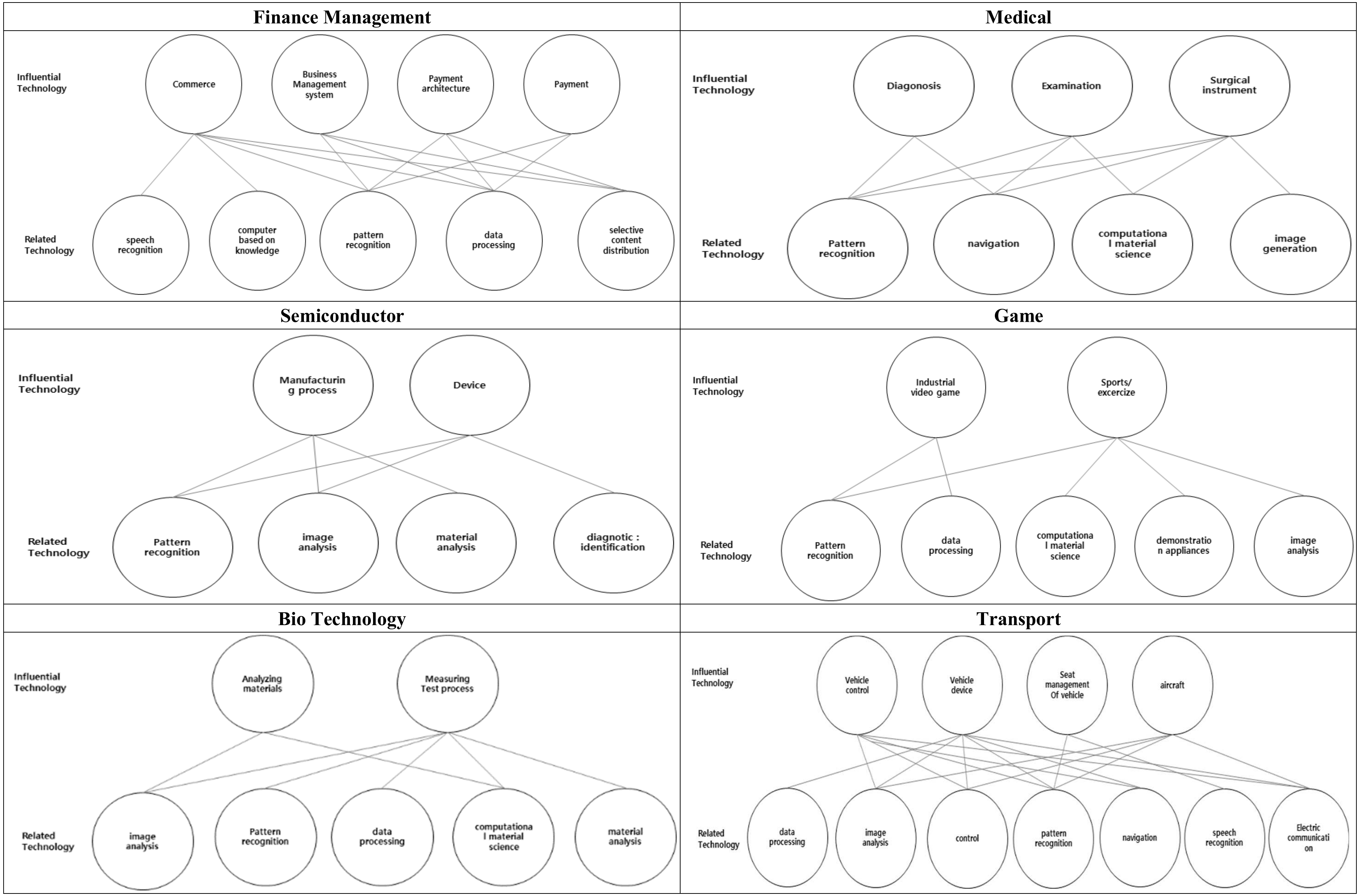

Fig. 1 Ties according to each hum in IPC network

Additionally, these firms should actively seek out and capitalize on the potential for generating new ventures in emergent domains linked to AI technology that remain untapped. Companies specializing in AI should focus on creating versatile core technologies adaptable across multiple sectors, considering the prevailing trends of AI convergence within these industries. The universally applicable AI technologies identified for various sectors in this research provides valuable guidance. When it comes to policymaking, there is a need to develop AI-related research and development strategies tailored to each industry that prioritizes long-term, sustainable societal progress rather than merely short-term tech advancements and economic expansion. This study has shed light on the network structure of various sectors of AI convergence.

Future research suggestions based on the limitations of this study are as follows. This study examined AI patents based on three categories of technology. Even though we tried to find the ties of the network using three categories of technology, future studies could expand the spectrum of categories of technology or industries to understand the comprehensive structure among technologies and AI industries. In doing so, scholars could gather patent information from a broader range of AI industry and technology categories. On the other hand, future studies could delve deeply into each industrial sector respectively so that we could track network dynamics and evolution. We could also examine contrary viewpoints on ties in the IPC network, which is not covered in this study. Since this study focuses on the technology and industrial sectors with high centrality measures and strong tie values, research on the technology and industrial sectors that have low centrality and tie values is necessary. This work could provide another piece that could help us understand the characteristics of AI convergence with low centrality and value.

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