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Submission for ACM Papers

Artificial intelligence in construction industry: Evolutionary analysis of technology convergence

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The swift evolution of digital technology has spurred numerous industries to enhance their innovation competencies. The construction industry, characterized by low levels of digitalization, is in dire need of incorporating digital technologies. Artificial intelligence (AI) technology is the preeminent technology in the field of digitalization, and its integration with construction technologies is expected to yield innovative achievements. However, the majority of extant research concerning the implementation of AI technologies in construction is based on analyses of scholarly papers and literature reviews. Only a limited number of studies employ quantitative patent data to explore the convergence degree of AI and construction technology. This paper measures the degree of technological convergence using patent data and graph convolutional neural networks (GCN) based on patents. The spatiotemporal evolution characteristics of technological convergence in the AI and construction fields are analyzed. Technology convergence degree is studied to identify key fields that promote the convergence of AI technology and construction technology. This study improves the relevant theoretical methods for identifying technological convergence and can help industry regulators focus on AI and construction technology convergence fields with potential and value, and formulate policies to promote digital development in the construction industry.

Keywords and Phrases: Technology convergence; Artificial intelligence; Graph convolutional network (GCN).

1 INTRODUCTION

Industries must keep up with the trends of the times to ensure their development (Chen and Ying, 2022). The world is currently undergoing the fourth industrial revolution - Industry 4.0, which aims to integrate digital information technology into traditional industrial practices to achieve digitalization, intelligence, and automation of industries, and drive industry transformation and upgrade (Chircu and Mahajan, 2009). However, according to McKinsey's digital globalization index, the construction industry is one of the least digitized industries in the world. There are various reasons for the phenomenon mentioned above in the construction industry, like excessive reliance on manual labor and low levels of technology. These factors have resulted in an extremely slow innovation process within the field of construction. Overall, the lack of digital professional knowledge and technology in the construction industry has led to issues such as low cost-efficiency, uncertainty in decision-making and management, project delays, and safety risks. Therefore, its future development must be driven by the integration of digital technologies.

Artificial Intelligence (AI) technology is the most important technology in digitalization, which can predict and model data through AI functions such as machine learning, deep learning, and neural networks (Bughin *et al.*, 2017). The combination of AI technology and construction can reduce construction costs and help building enterprises achieve sustainable development goals(Tekkeşin, 2019). Technology convergence has been recognized as a crucial driver of innovation. The convergence of technologies in the construction field with artificial intelligence is poised to be the mainstream of technological innovation in the future. Therefore, understanding the current convergence trends between artificial intelligence technologies and construction technologies is crucial to enhance the development of intelligent innovation technology in construction, and stimulate the creation of new products and services. It is of great significance for improving the digitalization level of the construction industry.

The existing research has the following limitations: 1) In terms of research content, many studies rely on literature reviews to identify the applications of AI and the construction industry, and lack quantitative analysis of the integration using patent data; Previous studies have mostly listed the application of AI technology or its subfield technology in the construction industry from a macro perspective, such as through simple enumeration, without providing specific application fields that can promote the integration of AI and construction technology. 2) Most of the previous studies identifying technology convergence focus on IPC code networks lacking identification based on patent textual data. The concept of technology convergence refers to the overlap occurring between two or more fields (Curran and Leker, 2011). Textual overlap is a more accurate representation of technology convergence. Patent data is considered one of the main indicators for measuring technological innovation, and most modern innovative inventions are tracked and recorded through patent data (Seo, 2022).

To address the limitations of previous studies, this paper utilizes patent textual data and employs a graph convolutional network (GCN) to aggregate patent network features and measure the degree of technological convergence. The characteristics of the technology are not only determined by the technology itself but are also influenced by the technology its number of times cited citations, shown as a network feature. This study also analyzes the spatiotemporal evolution characteristics of the technology convergence of AI and construction technology subfields from the perspectives of convergence degree and identify key convergence fields that can promote the digitization and intelligence of the construction industry. Identifying the convergence trends of AI technology in the construction field and identifying key technologies are of significant importance for discovering technological opportunities and providing development recommendations to the technical authorities of the construction industry.

2 LITERATURE REVIEW

2.1 Artificial Intelligence in Construction

AI technology has been widely applied in the architecture field, encompassing various aspects from design specifications to construction management, and health risk assessment. Figure 1 illustrates the development trajectory of AI technology. The earliest concepts of AI can be traced back to the 1940s, when McCulloch and Pitts proposed the neuron logic model (McCulloch and Pitts, 1990), and Turing introduced the Turing test (Turing test, 2009), which marked the birth of artificial intelligence. In the 1960s, AI technology was in its infancy. Stenson's research on the "architecture machine" (Steenson, 2022) laid the groundwork for the integration of AI in the architecture industry. However, the entire field subsequently experienced its first "winter." By the 1980s, emerging technologies such as expert systems and artificial neural networks propelled the practical application of AI. For instance, Miyao (Wei et al., 2022) used expert systems to establish fault tree models for detecting operational failures in construction machinery. Yet, AI technology faced its second "winter" thereafter; From the 1990s to 2010, advancements in the internet led to breakthroughs in computer hardware, fostering higher computational capabilities and driving AI research forward. The application of technologies like neural networks and fuzzy logic facilitated a steady progression phase for AI. For example, Lin et al. (Gupta, Kewalramani, and Goel, 2006) used neural networks to predict concrete strength, while George et al. (Georgy, Chang, and Zhang, 2005) applied neurofuzzy systems to forecast structural engineering performance; Since 2010, AI technology has entered a rapid development phase. The advent of frontier technologies such as deep learning, machine learning, data mining, and natural language processing has significantly broadened and deepened AI applications in the architecture field. These applications now span health and safety monitoring, risk prediction, cost estimation, process optimization, and material structure design.

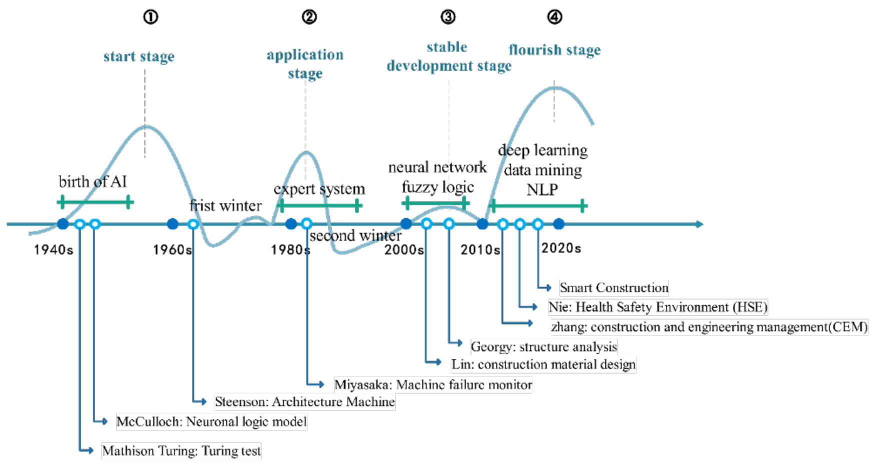

Figure 1. Overview of the development of artificial intelligence applications in construction.

2.2 Technology convergence exploration

2.2.1 Technology convergence Network

Technology convergence refers to the merging of boundaries between unconnected industries, technologies, fields, and markets, causing an overlap. This notion of technology convergence was initially developed by Kodama (Caviggioli, 2016). Research concerning technology convergence involves various disciplines and industries, showcasing the integration of different fields and providing high innovation value. The employment of patent data can create patent networks and effectively detect the flow of knowledge. Currently, the examination of technological convergence mainly employs three strategies to construct patent technology networks and examine technological convergence: co-citation, co-occurrence, and semantic-based approach. The semantic-based approach can be designed through algorithmic language programming to convert vast amounts of patent text into structured data, systematically measuring the technological convergence degree based on semantic similarity. This method has several advantages: 1) Semantic information is not constrained by time lag. It is necessary to take time for emerging knowledge to convert to patents, so the representation of patents usually has a lag time (Kim and Sohn, 2020). 2) Semantic networks can include more information compared with co-occurrence or co-classification networks. The co-occurrence or co-classification network of patents is often limited by the patent itself and its classification system, and the type of technology represented is specific (Zhu and Motohashi, 2022). There are emerging technologies that have not yet been incorporated into the IPC classification system, which may lead to a loss of information on emerging technologies.

2.2.2 Technology convergence degree measurement

Quantitative measurement of technological convergence identification is of great significance for detecting technological patterns and driving the development of convergent technologies. The measurement indicators obtained through technology convergence can intuitively reveal the overall trend of technology convergence and provide strategic suggestions for industry development. The research on measuring the degree of technological convergence is mainly divided into two perspectives. The first is to construct measurement indicators based on the patent attributes within the technological field. Liang used the Hirsch-index to calculate the proportion of fusion patents to all patents to represent the degree of technology fusion; Luan constructed a technology co-classification index based on the Jaccard coefficient to measure the technological relevance(Luan, Liu and Wang, 2013). The second approach is to measure the convergence degree by constructing network indicators from a technological network perspective. This article constructed a technology network based on the semantic method, calculating the cosine similarity of the feature vectors of the technology fields trained by GCN can clearly express the degree of similarity between technology fields.

3 METHODOLOGY

3.1 Data collection and preprocessing

This research involved extracting data relevant to AI and construction technology patents from the IncoPat database spanning the last decade (2013-2022). To procure patents that accurately represent AI and construction technology, it was crucial to design retrieval formulas based on classification principles. AI patents were discovered using a blend of "IPC (International Patent Classification) + CPC (Cooperative Patent Classification) + keywords". The search formula BLOCK_AI was constructed following the WIPO technology trend – AI (*Technology Trends 2019: Artificial Intelligence*, 2019), which integrated the use of IPC, CPC, and keywords for AI patent retrieval. After going through comprehensive review articles that associate AI with the construction industry(Baduge *et al.*, 2022; Ding, Ma and Luo, 2022), the search formula BLOCK_CS was implemented for the construction field.

The process for determining these keywords is as follows: First, this study refers to the AI trend report issued by WIPO (Technology Trends 2019: Artificial Intelligence). Additionally, the Stanford University AI Index Report 2022 (Zhang and Maslej, 2022) demonstrates the development trends of the ten most significant topics in AI-related publications since 2010. By integrating insights from these two reports and conducting expert interviews, eight final AI keywords were identified. The process for selecting keywords in the field of construction is as follows: This study references several review articles (Abioye *et al.*, 2021; Pan and Zhang, 2021; Chen and Ying, 2022; Jacobsen and Teizer, 2022) on the application of artificial intelligence technologies in the construction field, summarizing the main application scenarios of AI in this area. Given that patent classifications in the construction field are not as detailed as those in review articles, this study also incorporated expert interviews to summarize eight keywords. These eight keywords encompass the classifications from previous reviews but are presented from a more macro perspective."

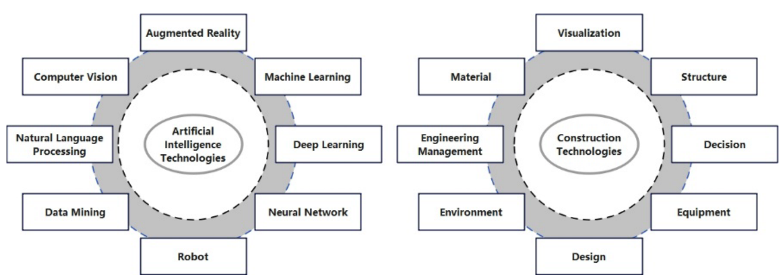

Figure 2. Artificial Intelligence and Construction Keywords

After defining the subfields, every patent will have a label based on semantic including relationships. If the abstract or title of the patent contains the keyword, the patent is labeled with that keyword, and it belongs to the corresponding subfield. A patent can be assigned multiple labels. Thus, we can obtain a network graph of patents and keywords based on the assigned labels. The construction process is shown in Figure 3.

Index	ID	Title	Abstract	Sorts	IPC Classification	Number of citations	Number of citations received
1	JP7219180B2	Method of creating a borehole prediction model for shield tunneling method	In order to provide a system that can be managed so that the shield excavator reflects the "factors" of the shield excavator at the construction site,……**machine learning**……	Invention authorization	**E21D G06N**	7	1
2	TW202303430A	Automated analysis method and its system for submerged shield tunnel engineering	An automated analysis method for submerged shield tunnel engineering and its system…… **machine learning** ……	Invention authorization	**E21D G06Q;**	0	0

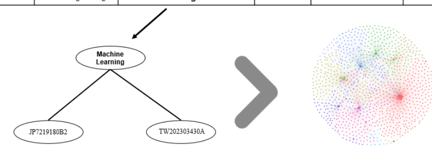

Figure 3. Technological network based on semantic relationship

3.2 GCN method

The technological network was constructed based on semantic inclusion relationships in section 3.1. This allows for the measurement of the overall characteristics of patents through the relationships between nodes and edges, thereby enabling an accurate assessment of the degree of technology convergence. GCN is applied to extract the features from the technology because the training process of GCN will aggregate the characteristics from neighboring nodes. The research approach employed in this work builds upon the methodology established in Zhu's study (Zhu and Motohashi, 2022), which adopts a GCN to understand and analyze the representations of keyword vectors w_t^t. The process initiates with the implementation of the word2vec technique, which is designed to generate word vectors for every individual word present in the abstract of the patent. The establishment of each patent vector at the fundamental layer of the GCN is accomplished by averaging out all the word vectors that appear in the patent abstract. This not only creates a comprehensive picture of each patent derived from its abstract, but it also assures a deeper understanding of the context, through keywords, expanded by the neural network in the analytical process.

$$H_i^{(1)} = \frac{1}{n_{A_i}} \sum_{t \epsilon A_i} w_i^t \quad (1)$$

$H_i^{(1)}$ represents the i-th patent vector, A_i represents the abstract, n_{A_i} represents the number of words, and w_t^t represents the word vector of the t-th word in the i-th patent abstract. Afterward, by gathering the neighboring patent node vector attributes, the second layer of the GCN is trained to yield keyword vectors.

$$H_j^{(2)} \;=\; \sigma\left(\frac{1}{N_j} \sum_{i \epsilon N_j} W^{encoder} H_i^{(1)} + b^{encoder}\right) \quad (2)$$

$H_j^{(2)}$ represents the j-th keyword vector in the second layer of GCN, σ is the activation function, N_j represents the number of neighboring patent nodes around the j-th keyword node, and W and b are the encoding weight matrix and bias optimized by GCN training.

3.3 Technology convergence degree

Employing the GCN methodology, vector representations of patents as well as their corresponding subfields are obtained. For any given patent, its association with the keyword vectors of a specific subfield can be measured by understanding the cosine similarity, thereby determining the patent's feature vector within that defined subfield. This results in a more insightful understanding of the patent's relevance and alignment with that subfield. We can represent the feature vector for a specific 'i-th' patent within the context of the 'j-th' subfield as follows:

$$P_{i-j} = \cos < P_i,\ K_j > \quad (3)$$

The vector represents the ‘i-th’ patent after training with GCN, and the vector represents the ‘j-th’ subfield after GCN training.

This paper probes into patents that are associated with two distinct sectors: Artificial Intelligence (AI) and Construction (CS) technologies. Each patent has an association with a feature vector in either the AI or CS field, which is known as technological intensity. This technological intensity demonstrates the degree of convergence that a patent shares with either of the two mentioned technological sectors. The capability or technological advantage of a patent in relation to the AI or CS sector is measured via the highest cosine similarity between the patent and all subfields that come under the umbrella of the specific AI or CS sector.

$$P_{i,AIintensity} = \max_{j \epsilon AI} P_{i-j} \quad (4)$$

$$P_{i,CSintensity} = \max_{j \epsilon CS} P_{i-j} \quad (5)$$

The degree of convergence between subfields is calculated directly using cosine similarity on the keyword vectors. Specifically, the degree of convergence $P_{m,n}$ between the ‘m-th’ subfield in AI technology and the ‘n-th’ subfield in Construction technology is given by:

$$P_{m,n} = \cos < K_m, K_n > \quad (6)$$

The degree of convergence between the two domains can be obtained by taking the average of the degree of convergence between their respective subfields. Therefore, the degree of convergence (Cov) between AI technology and Construction technology is given by:

$$Cov = mean\left(\sum_{m=1}^{8}\sum_{n=1}^{8} P_{m,n}\right) \quad (7)$$

4 RESULT AND DISCUSSION

4.1 Model validation

Table 1. Comparison results of models.

Models	AP-TFIDF	Word2vec	Doc2vec	Word2vec&GCN	Models	AP-TFIDF	Word2vec	Doc2vec	Word2vec&GCN
(1)Accuracy					**(2)Precision**				
RF	0.729	0.736	0.768	**0.769**	RF	0.693	0.709	0.735	**0.779**
LR	0.815	0.816	0.779	**0.790**	LR	0.803	0.804	0.763	**0.810**
DT	0.767	0.764	0.726	**0.764**	DT	0.740	0.733	0.699	**0.803**
KNN	0.745	0.756	0.740	**0.760**	KNN	0.718	0.738	0.724	**0.810**
(3)Recall					**(4)F1-score**				
RF	0.729	0.736	0.768	**0.966**	RF	0.704	0.717	0.715	**0.863**
LR	0.815	0.816	0.779	**0.941**	LR	0.801	0.803	0.725	**0.871**
DT	0.767	0.764	0.726	**0.909**	DT	0.743	0.730	0.709	**0.853**
KNN	0.745	0.756	0.740	**0.890**	KNN	0.726	0.744	0.730	**0.848**

To ensure the word2vec and GCN models outperform other models, this study compares them with other models, including AP-TFIDF, Word2vec, and Doc2vec. The classification accuracy of embedding models is compared on four machine learning methods, including Random Forest (RF), Decision Tree (DT), Logistic Regression (LR), and K-Nearest Neighbors (KNN). Four indicators are applied for classification assessment: accuracy, precision, recall, and f1 score. The result of the comparison is shown in Table 1. It is evident that the word2vec-initialized vectors, combined with GCN training, better represent the textual information of the original patents and keywords. Although the accuracy of this model may not have improved significantly, it shows a clear advantage over other models in terms of recall, precision, and F1 score metrics.

4.2 Patent level

Based on the measurements of each patent in section 3.2, the technological intensity of each patent in the AI and construction fields serves as coordinates. We divided the last decade into five periods to investigate the convergence of patent technologies. Fig.5 illustrates the convergence situations for the time periods 2013-2014 and 2021-2022.

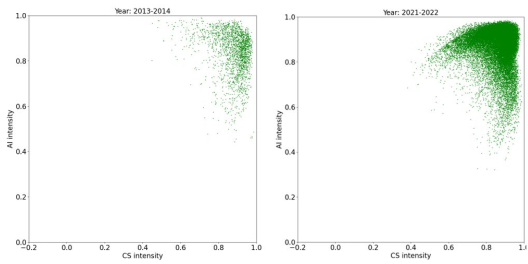

Figure 4. Patent convergence intensity

Each node represents a patent, the x-axis represents a patent's technological intensity in the CS (construction) field, and the y-axis represents a patent's technological intensity in the AI field. Overall, with the progression of time, the density of patents in the five stages within the graph increases. Patents located near the diagonal line display a high level of both AI and construction technological intensity, which suggests a gradually growing convergence of patents in the AI and construction fields. This indicates the rapid development of AI technology, and its application in construction technology has progressed, however, it's not quite mature yet. The majority of the newly added patents have relatively lower AI technological intensity.

4.3 Field level

Utilizing the formula delineated in Section 3.2, an overall convergence degree between the fields of AI technology and Construction technology has been computed. The fluctuations of this convergence degree over time are exhibited in Figure 5.

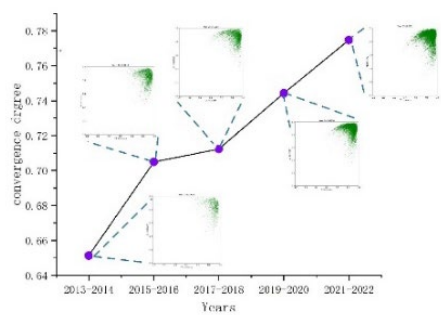

Figure 5. Evolutionary Convergence Trends of AI and Construction Technology

After quantifying the convergence degree of AI and construction technology, it can be observed that the convergence trend of the two fields has been linearly increasing overall, particularly noticeable after 2017. After 2010, we entered the third spring of AI where its technology is gradually merging with construction technology, stimulating the emergence of new technologies in the construction field. This is reflected in the increasing number of patents year by year. Simultaneously, the annual growth trend of convergence is similar to the results observed through patent technological intensity.

4.4 Subfield level

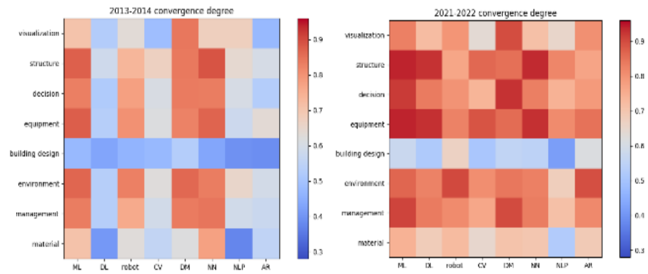

Figure 6. Convergence Degree Matrix

The convergence degree of sub-fields within AI technology and Construction technology is calculated based on trained keyword vectors obtained through semantic similarity methodology. There are eight sub-fields for both the AI technology and Construction technology areas, and only the technological fusion situation between each pair of domains is considered, resulting in 64 convergence combinations altogether. The convergence degrees of these 64 combinations are visualized. The convergence degree for the periods 2013-2014 and 2021-2022 is shown in Figure 6.

The vertical axis of the matrix represents the eight sub-fields of construction technology, and the horizontal axis represents the eight sub-fields of AI technology. The color of each matrix block represents the convergence degree of the corresponding fields. On the whole, with the passage of time, the convergence degree of AI sub-fields and construction sub-fields has been growing year by year. The sub-field related to Building design has always had a low degree of convergence with all AI technology sub-fields. Although there has been a slight increase, it is generally below the average convergence level. From 2013 to 2014, the convergence degree of most AI technology sub-fields such as deep learning, computer vision, natural language processing, and augmented reality with any construction technology sub-field was quite low. By 2021-2022, these AI technology sub-fields have achieved a higher degree of convergence with all construction technology fields.

5 CONCLUSION

Exploring the convergence relationship between AI and construction technology, along with their subfields, can uncover patterns and laws of technological development, facilitate the discovery of new technological directions and integration trends, and support the formulation of research and development policies and plans. By identifying key convergence portfolios from the perspective of convergence degree, our approach provides more persuasive results.

This study employs patent data trained by the GCN method to measure the convergence degree between AI technology and construction technology based on a technological network constructed through semantic inclusion relations. It then analyzes the spatiotemporal evolution characteristics of the technological portfolios in these two fields. Key convergence portfolios are identified, offering direction for the future integration of AI technology into the construction industry. The results indicate that the convergence of AI and construction technologies has become an unstoppable trend. In recent years, most new patents exhibit high intensity in construction technology. In the future, moderating the intensity of construction technology development will allow for a deeper integration of construction patents and AI technology, thereby enhancing the AI technology intensity in construction technology to ensure a balanced integration of the two fields.

Furthermore, the convergence degree trend of AI and construction technology subfields mirrors that of the overall fields. Notably, later-developed convergence portfolios such as deep learning & structure, deep learning & equipment, computer vision & equipment, and augmented reality & environment show greater potential among portfolios with a higher degree of convergence. This paper identifies key subfields and key patents in the convergence of AI and construction technology, offering recommendations to regulatory authorities in the construction industry. Additionally, it can facilitate collaboration between AI-related enterprises and construction companies, guiding the future development of these companies. This study also has certain limitations. Firstly, the accuracy of the selected keywords is critical; these keywords must aptly represent the characteristics of the field. Moreover, in terms of measuring convergence degree, this paper only uses the abstract and title information of patents; future research could benefit from utilizing the full text of patents.

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