Automating the Modular Construction Process: A Review of Digital Technologies and Future Directions with Blockchain Technology

Abstract

Modular integrated construction (MiC) method has come to limelight in recent years due to its enormous potentials. Although several digital tools and technologies (DTT) have been employed in MiC projects, no previous research study has critically reviewed and analysed their implementation in MiC projects. The current study addresses this gap using a three-tier research approach– data curation, science mapping, and systematic analysis to evaluate modular construction research studies. The findings revealed minimal application of DTT in the MiC prefab transportation phase and the potentiality of blockchain and other integrated DTT for use in MiC projects. Globally, Canada, China, and the USA are the leading countries that have applied DTT in MiC projects. Also, simulation, building information modelling (BIM), and optimization algorithms are the most frequently deployed DTT in modular construction. This study has provided valuable insights into the digital technologies adopted in MiC projects and potential areas for its future use in modular construction.

Keywords: Blockchain technology; digital tools; modular integrated construction; prefabrication; technologies.

Nomenclature

BCT	Blockchain technology
BIM	Building Information Modelling
BIM-OfA	BIM-Based Optimizer for Assembly
DfMA	Design for Manufacture and Assembly
DTT	Digital tools and technologies
MCR	Modular Construction Research
MiC	Modular Integrated Construction
PSO	Particle Swarm Optimization
RFID	Radio Frequency Identification

1. Introduction

MiC projects form a critical mass and are vital to the overall development and sustainability of the built environment, and much attention has been given to it in recent years. MiC is the process and technology of creating 3D-volumetric furnished modules in off-site facilities and transporting them to the site for proper assembling and installation. MiC is primarily carried out in phases of prefab manufacturing, transportation, and on-site installation [1,2]. Each of these phases is pivotal to the overall development of the prefabricated buildings and facilities. Prefab manufacturing dates back to the 17th century, when manufactured goods were transported from one place to another [3]. The MiC processes have evolved over the past years and have reached a point where technology is becoming a major fulcrum and centre point.

The relationship between MiC processes and technology is vital, and the use of these DTT is a significant enabler. The different digital technology tools are indispensable to the overall automation of the offsite construction processes. For instance, integrating BIM into the prefab manufacturing phase has significantly increased the productivity of manufacturing processes [4]. Through the application of real-time integrated frameworks and perspectives ranging from organization, coordination, implementation, BIM has been identified as a viable DTT by [5], and its benefits and importance are well outlined in the extant literature [6,7]. Achieving automated modular construction processes is made easy through the instrumentality of several digital technologies, which has strengthened the methods and mechanisms of implementing modular construction in each of its phases. Machine learning and generic algorithms that are data-driven have helped drive the growth and implementation of the MiC through supervised learning and training. The faster training that the radial basis function illustrated in [8] when used in relevant DTT, which is data-driven, enhances their suitability for MiC processes.

Moreover, as demonstrated by Yin et al. [9], the application of RFID and personal digital assistants facilitate real-time information sharing with all stakeholders with a resultant improvement in the overall construction process. Therefore, automating the processes involved in modular construction is of prime importance to its overall development and sustainability. At the same time, digital technology tools provide a great path for this developmental agenda. In a similar context, [10] emphasized the need for the proper automation of prefab manufacturing to lay a strong foundation for the remaining phases. In another instance, the multilayer perceptron neural network proposed by Pan et al. [11] to drive the modular construction process at the prefab transportation phase was trained with a backpropagation algorithm, and defective modules during transportation were detected in real-time. This distinct technology in the transportation phase saves time as the faulty modules can be fixed in real-time or replaced before arriving at the on-site assembly. Thus, integrating innovative technologies in modular construction works offers wide-ranging possibilities because construction work can be carried out very fast without much delay. Damages and rework can also be reduced to the barest minimum when appropriate digital tools are employed.

A number of studies in the extant literature have reviewed modular construction, some of which are tabulated by [12]. Other recent review studies include [13] and [14], which conducted scientometric analysis and qualitative analysis of the offsite construction articles. Other tailor-made reviews focus on specific research areas in MCR, such as sustainability [10] and critical drivers for its adoption [15]. These studies used varying research databases such as Web of Science and Scopus. At present, studies on the use of DTT have only focused on its application in a particular case study, and as at the time of data curation in this study; no paper has examined and reviewed the implementation of DTT in modular construction projects; nor analysed its trend, structure, and knowledge areas.

Given the above, the current study aims to critically explore and conduct an in-depth review of the digital tools and technologies applied across the MiC phases. The key objectives to be achieved are: (i) identify and track the evolution, trend, and structure of DTT application in MCR. (ii) Reveal the gaps in the implementation of DTT across the MiC project phases. (iii) Investigate the pattern or method of the application of DTT employed in MCR - while discussing its related strengths (benefits) and weakness (limitations) of the DTT in relation to their use in MCR. (iv) Explore the potentiality of blockchain technology as an enabler for MiC projects – and how it could enhance these DTT strengths and ameliorate their weakness. As expatiated in the next section, a three-tier research approach would be employed in achieving these defined objectives.

Subsequently, the scientometric analysis and a review of the research corpus will be discussed in section 3. In contrast, section 4 would expatiate on the various DTT and their implementation across the MiC phases. Section 5 outlines blockchain's potentiality and prospects in MiC projects, while section 6 concludes the study. It is expected that the findings of this paper would be useful to its readers by facilitating their understanding and interest in applying DTT in MiC projects and other construction methods towards enhancing the digitalization of the construction industry.

2. Research Methodology

A multi-stage research approach was used in the present study to critically explore and analyse the digital tools and technologies adopted in the extant literature to automate the modular (offsite) construction process. The first stage of the research approach is data curation, followed by science mapping and systematic analysis (see Figure 1).

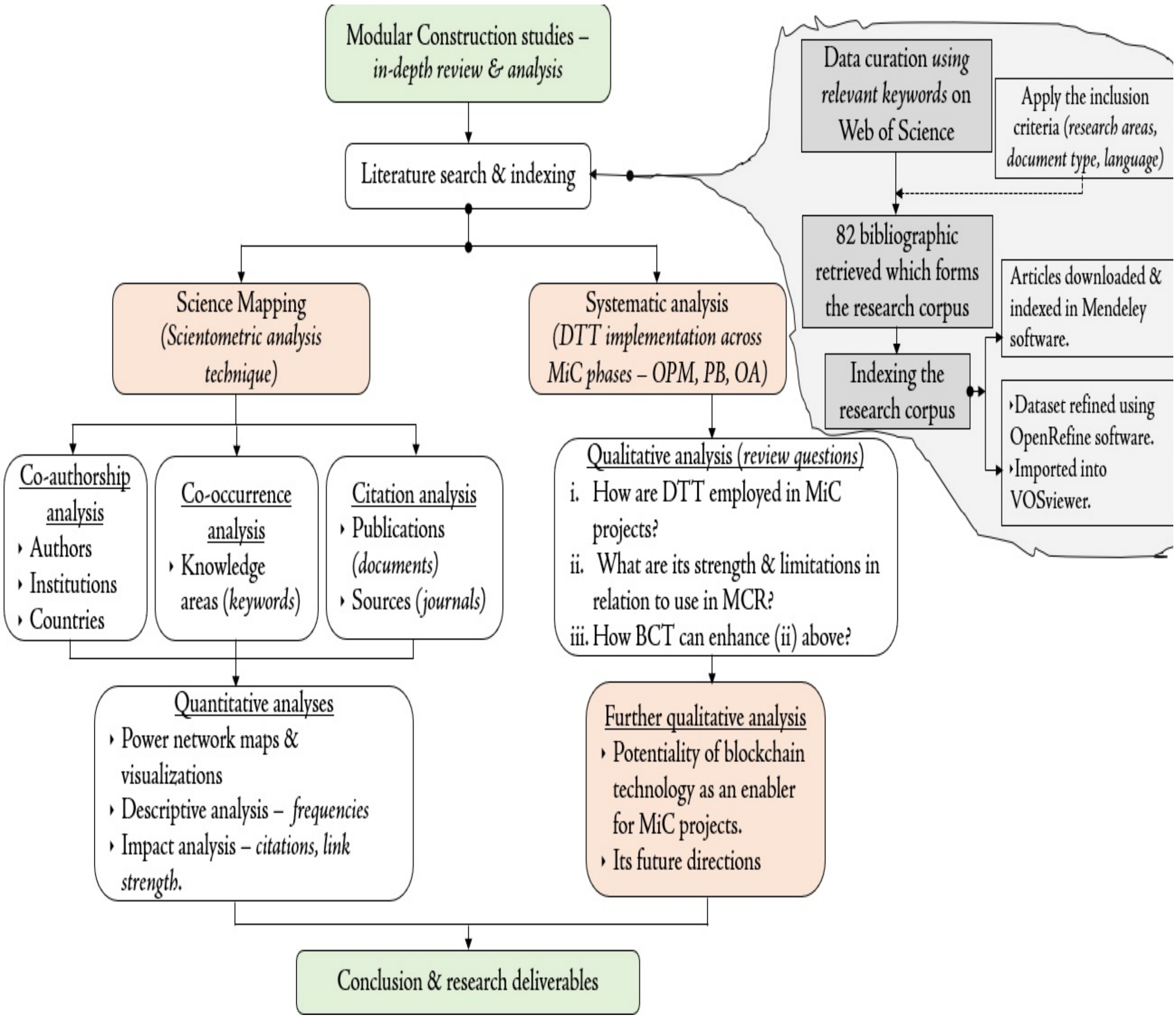


Figure 1: Outline of the research design

2.1 Data curation

Data curation involves the process of retrieval, management (discovery and analysis), and organization of data collected from sources (databases/repositories). It allows for the preservation and maintenance of data quality [16] and adds value to digital research data. More so, digital tools and machine learning algorithms are often employed to facilitate data re-use, sharing, and manipulation using digital tools and machine learning algorithms. Data curation was used in this study to extract data from a scientific research database. Several research databases are available to the authors, such as Google Scholar, Scopus, Web of Science (WoS), ProQuest, and Microsoft Academic. Olawumi et al. [17] considered WoS and

Scopus more reliable research databases with broader coverage. An in-depth review of Scopus and WoS databases by [18] shows a significant overlap in their publication records. Moreover, the WoS database was selected because it contains more influential and comprehensive records and because of its scientific robustness [19–21].

Afterwards, research data were retrieved from WoS using an iterative search process to get a reliable result. Search keywords used are - "*off-site construction*" OR "*modular construction*" OR "*prefabrication construction*" OR "*modular integrated construction*" OR "*modular buildings*" OR "*prefabricated building*" OR "*offsite construction*" OR "*precast concrete building*" OR "*precast construction*" OR "*prefabricated housing*" OR "*off-site manufacturing*" OR "*offsite manufacturing*" OR "*volumetric construction*." The time span for the search was between 1970–2020. The retrieved publication records were limited to journal papers – as the article category is regarded as a reputable and certified knowledge source [22] and more comprehensive [23]. The data was further refined to include articles related to "engineering," "construction building technology," and "architecture" research areas, which resulted in 450 bibliographic records, which are indexed in Mendeley reference manager and saved as a marked list on WoS. Greiner and Robart published the first paper on modular construction in 1970, which focused on electric heating adapted for modular buildings [24].

Meanwhile, to align the retrieved data with the research aim, in-depth content analysis of the research corpus – especially the topic, abstract, keywords – was further carried out to identify publications that solely employed digital technologies and tools for modular construction. A total of 82 bibliographic records (year span= 1992–2020) conform to this selection criteria and were included in the final research corpus; and indexed in Mendeley reference software. However, papers that applied questionnaire surveys, interviews, and discussing these technologies were excluded.

2.2 Science mapping

The science mapping method is a useful and proven approach to picture dynamic patterns in bibliographic records and databases [25]. It provides reliable diagnostic tools to conduct, link, and process literature concepts, which are often overlooked in a manual review process [26]. More so, science mapping involves three independent but overlapping research techniques – bibliometric analysis, scientometric analysis, and informatics [12]. Readers interested in in-depth information on these three techniques can consult relevant studies *such as* [27,28]. According to [12], the scientometric analysis includes bibliometric methods. Hence, it was adopted as the primary technique for the study's science mapping.

Several scientometric software is available for use, such as VoSviewer, CiteSpace, Gephi, BibExcel, and the like [25]. The VoSviewer and CiteSpace are the most widely used tools for scientometric reviews in the extant literature overlapping features. However, the VoSviewer was adopted in this study as it is more user-friendly [29] and contains features useful in this study analysis such as (i) distance-based visualizations; (ii) smart-moving clustering algorithm; and (iii) full and fractional counting methodology [30].

A range of scientometric techniques was conducted on the indexed 82 bibliographic data using the VoSviewer software in this study, such as co-authorship analyses (authors, organizations, and countries analyses), co-occurrence keywords, citation analyses (document and journal co-citation analyses), and keywords clustering. A few more scientometric techniques are achievable via the VoSviewer. Still, these identified techniques are adequate to achieve the study's objectives. Extant literature [21,30,31] provides in-depth descriptions of these scientometric techniques. More so, these scientometric analyses generate relevant network maps on the VoSviewer software, which provides more useful information and measures of the network. The science mapping approach forms the quantitative analysis stage of this study.

2.3 Systematic review

Systematic reviews (SR) are not a literature review in the traditional sense, and it involves examining existing studies, evaluating scientific contributions, and synthesizing the relevant data. Hence, this SR process allows for reasonable and clear conclusions to be reached – "*on what is and is not known*" [32]. Also, per [33], SR complements other reviews, including science mapping by a key element of evidence-based research.

The steps for a systematic review include: (1) frame the review questions; (2) identify relevant studies; (3) assess the research corpus quality; (4) summarize the research evidence and resolve literature conflicts, and (5) interpret the findings (*clarify the studies' relative strengths and weakness*) and provide recommendations for future research [33,34]. The formulation of the research question and the research corpus's size are fundamental aspects for an SR to ensure any applicable conclusion is reached [34].

The key ***research/review questions*** examined in the SR aspect of this paper are: (i) how are digital tools and technologies (DTT) employed for modular construction research (MCR) in the literature? (ii) What are the related strengths (benefits) and weaknesses (limitations) of each DTT in relation to its application in MCR? (iii) How can blockchain technology (BCT) enhance these DTT strengths and ameliorate their weakness? (iv) What is the potentiality of BCT as a new collaborative system in modular integrated construction (MiC) projects? Moreover, the research evidence from the review questions (i) – (iii) would be discussed based on the three phases of typical MiC projects: the offsite prefab manufacturing phase, prefab transportation, and the onsite assembly phases.

3. Research Findings: Scientometric analysis

This section discusses the scientometric analysis results based on the research approach outlined in section 2.1 and Figure 1.

3.1 General overview of the research corpus

The two sets of bibliographic records highlighted in section 2.1 were analysed in this section.

Publication years: The first implementation of MiC in the construction industry dates to the 1960s. However, the first few papers on MiC concepts were published between 1970–1990. The first paper that dealt with applications of digital technologies for MiC projects was in the year 1992 by [35]. They developed an expert scheduling system for MiC projects named "CONSCHED." However, there was no sporadic interest in MiC until this last decade (2010 – to date); before this, there were only 59 MiC articles (pre-2010) and just 7 MiC articles that applied technological tools in MiC (TA-MiC) projects.

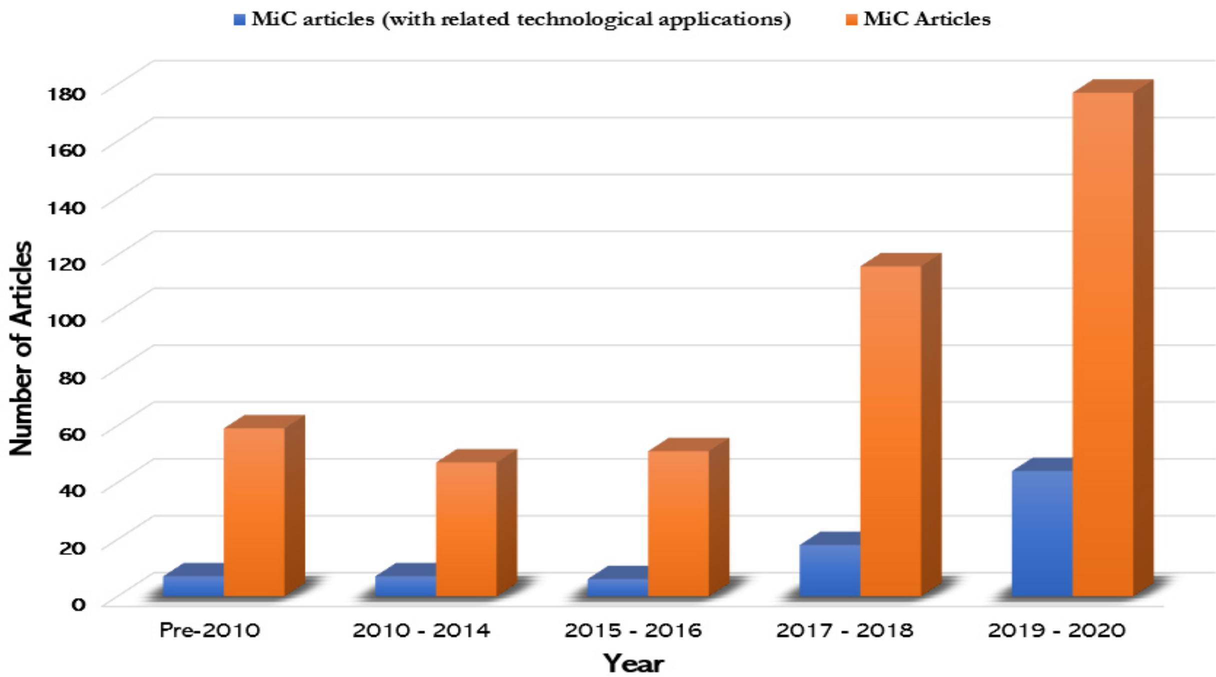


Figure 2: Distribution of published MiC research articles in 1972–2020
Data source: WoS database

More so, within the following 5-year range (2010–2014), there are 47 MiC articles and seven TA-MiC articles from the indexed WoS research corpus, constituting about 15% of the total MiC publications in the period (*see Figure 2*). In the year range (2015–2016), there was increased interest in MCR with 51 MiC papers, of which there are six TA-MiC articles (12⧺). Meanwhile, in the following two years (2017–2018), there was a very significant increase in MCR with 127↑ in MiC papers (127↑) and 200↑ in TA-MiC related articles (16⧺). In the last two years (2019–2020), there was a sustained interest in MCR in the built environment with a 53↑ and 144↑ increased growth rate in MiC and TA-MiC papers, respectively – of which there are 25⌗.

Note: ↑ – % increases compared to the previous year range. ⌗ – % constituent of TA-MiC papers in MiC publications within the specified year range.

Country and impact metrics: Further quantitative analysis of the WoS research corpus shows countries and regions with the widespread application of modular construction and TA-MiC (*see Figure 3*). The top five countries in MiC applications are China (122, 22), the United States (100, 16), Australia (77, 9), England (57, 7), and Canada (50, 25) – of MiC and TA-MiC articles, respectively. These countries constitute 68% of published MiC papers and 71% of TA-MiC articles when the co-authorship counting is normalized. MCR-related publications are well represented in the five regions (Table 1). North America, Asia, and Europe have made more research impact (h-index) regarding modular construction in the global built environment.

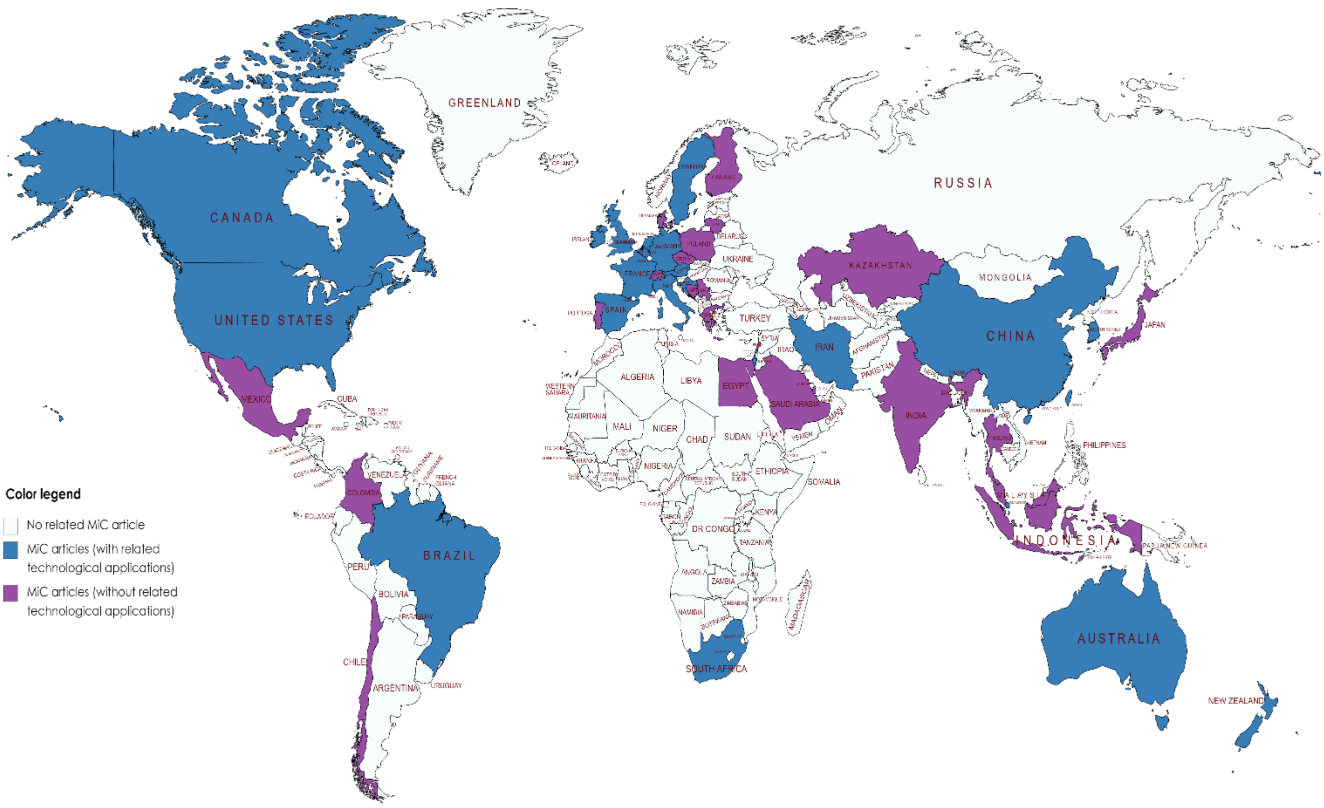


Figure 3: Global spread of MiC (inclusive of TA-MiC) related research publications
Data source: WoS Database

However, modular construction concepts are still at the early stages of adoption in Africa and South America, with three and nine MiC publications, respectively. The first MiC paper in South America was in 2007 [36], and it took more than a decade before the subsequent publication in 2018. Meanwhile, in Africa, the first co-authored MiC study was in 2013 but was based on a bridge project in Saudi Arabia (Asia). Afterwards, two articles were later published in the year 2017 and 2019.

Table 1: Impact metrics rating of regions

Regions (a, b)	Nr of MiC articles (*TA-MiC)	H-index (*TA-MiC)	Citations (*TA-MiC)	Citing Articles (*TA-MiC)
Africa (2, 1)	3 (1)	2 (1)	25 (16)	25 (16)
Asia (17, 8)	242 (45)	28 (12)	2974 (469)	1730 (387)
Europe (23, 12)	126 (22)	25 (8)	1854 (171)	1523 (154)
North America (3, 2)	143 (41)	24 (12)	2128 (337)	1634 (261)
South America (3, 1)	9 (3)	5 (1)	74 (22)	73 (21)

Note: a– number of countries with MiC articles; b– Number of countries with TA-MiC related papers; *TA-MiC articles; Nr– Number

3.2 Scientometric analysis

Prior to inputting the curated data from the WoS database into VoSviewer software for further quantitative analysis, the OpenRefine software was used to clean up, filter, and transform the data. For instance, there are several occurrences of the same term which connote the same meaning in the indexed WoS data, e.g. (i) "*Building Information Modelling*," "*Building Information Modeling*," "*BIM*"; (ii) "*off-site construction*," "*offsite construction*." Without data clean-up of such terms, it would affect the VoSviewer visualization and diminish the relevance of the produced network maps. Two clustering methods – *key collision and nearest neighbour* – on the OpenRefine application are used for the data clean-up (see Appendix A). About 29 term clusters were refined.

This section discusses the findings of the scientometric analyses as outlined in the research design (Figure 1) and section 2.2. Moreover, VoSviewer allows the direct use of WoS research data without further converting it before using the data to generate the power network map. Also, the variance in each item's node and font size within the generated networks indicates the number of articles published [30].

3.2.1 Mapping of the collaboration networks (*co-authorship analysis*)

Scientific collaborations among research scholars, industry practitioners, and government agencies breed expertise, bridge the digital divide, facilitate grants access, and increase productivity. The co-authorship analysis provides an in-depth understanding of the networks (authors, country, and organizations) and pinpoints the prolific research collaboration clusters.

Hence, this study maps the scientific collaborations of prolific authors, pre-eminent institutions, and leading countries in MCR research.

3.2.1.1 Prolific authors

A total of 253 authors published the 82 TA-MiC related research corpus used for the scientometric analysis. The scientometric analysis on the VoSviewer was undertaken as described in Appendix B. Figure 4 shows the generated collaboration network of the prolific authors with 14 links and total link strength (TLS) of 21.50. TLS indicates the total strength of the authors' cooperative relationships [30]. There are four research communities in the authors, with at least two authors forming the research circuit. However, the research circuit of Mohamed Al-Hussein is the most productive and prolific in the overall network with a TLS of 11, followed by those of Hosein and Ulrich with a TLS of 5.

The lack of cohesive collaborations among the authors is well-pronounced within the network map. This calls for more interdisciplinary research in the application of DTT in modular construction research. Rafiq and Pablo are the authors with recent publications in the TA-MiC field, as connoted by their yellow nodes (Figure 4). Table 2 provides more detailed information on the number of articles published by these prolific authors, their institutions, the number of citations received, the average publication time span, and the research expertise of the authors.

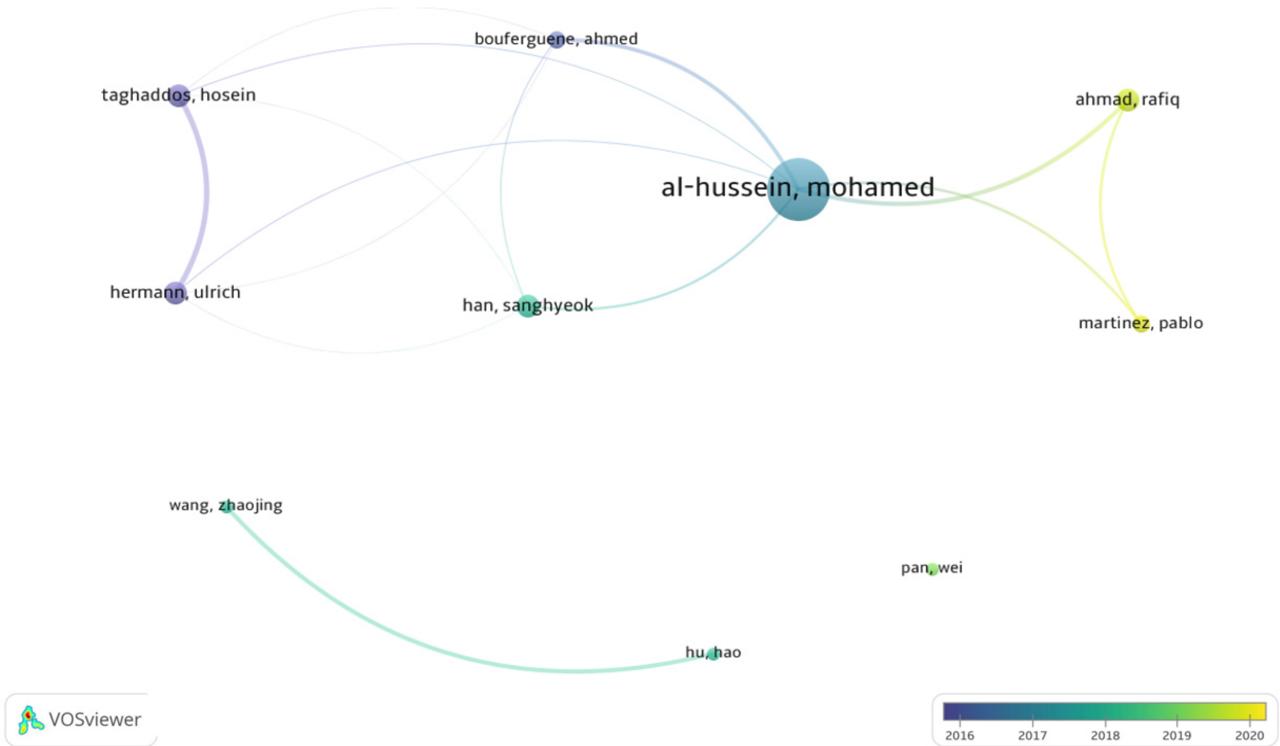


Figure 4: Network of prolific authors in MCR

As contained in Table 2, Al-Hussein has authored 14 publications that have impacted the TA-MiC research areas with 139 citations. His average publication year is 2017, with an average normalized citation value of 1.04. More so, these ten prolific authors' research expertise converge and ranges from 3D visualization and BIM, simulation, robotics, RFID, and blockchain for modular construction. Three main types of MiC are evidenced from their work: precast concrete assembly, steel frame assembly, and wood frame assembly.

Table 2: Quantitative analysis of the prolific authors in MCR

Authors (institutions)	Documents	Citations	Avg. Pub. Year	Avg. Norm. Citations	Research expertise
Al-Hussein Mohamed (University of Alberta)	14	139	2017	1.04	BIM and simulation for the steel frame and modular assemblies
Hermann Ulrich (PCL Industrial Management Inc)	5	67	2016	1.00	Automated crane planning and scheduling
Taghaddos Hosein (University of Tehran)	5	67	2016	1.00	BIM and simulation-based crane planning and optimization
Han Sanghyeok (Concordia University)	5	26	2018	0.65	3D-visualization and ergonomics in modular construction
Ahmad Rafiq (University of Alberta)	5	21	2020	0.98	Vision-based systems for steel frame assemblies
Bouferguene Ahmed (University of Alberta)	4	49	2016	1.01	3D-visualization and RFID for mobile cranes and modular assemblies
Martinez Pablo (University of Alberta)	4	15	2020	0.98	BIM and simulation-based systems for steel and wood frame assemblies
Hu Hao (Shanghai Jiao Tong University)	3	53	2018	6.06	RFID and blockchain-based systems for precast construction supply chains
Wang Zhaojing (Beijing Jiaotong University)	3	53	2018	6.06	RFID and blockchain-based systems for precast construction supply chains
Pan Wei (University of Hong Kong)	3	14	2019	0.77	Robotics and automated guided vehicles in modular construction

The mapping of the prolific authors can help guide researchers and other interested stakeholders in MiC projects to pinpoint the key authors to track so as to keep updated on relevant TA-MiC publications. It also provides useful information for potential future scientific collaborations in MCR.

3.2.1.2 Pre-eminent institutions

The next phase of the analysis examined the pre-eminent institutions active in applying DTT for MCR. The scientometric analysis was carried out as described in Appendix B. The active institutions' collaboration network, as revealed in Figure 5, has 14 links and a TLS of 18. The generated network shows a low level of collaboration among these pre-eminent institutions, as reflected by the scattered and less connected network nodes. Nevertheless, the strongest links exist between the pairs of (i) University of Alberta (TLS=8) and PCL Industrial

Management Inc (*a construction company in Canada* – TLS=5); as well as (ii) University of Alberta and Concordia University (TLS=4), and both research partnerships as a TLS of 2.5. This academic-industry technology and knowledge transfer are commendable and profound. They allow and sustain interest and investment in the field, especially those with the application of technologies [37,38]. It also provides insights into how research partnership policies can enhance the digitalization of the built environment, especially for MCR.

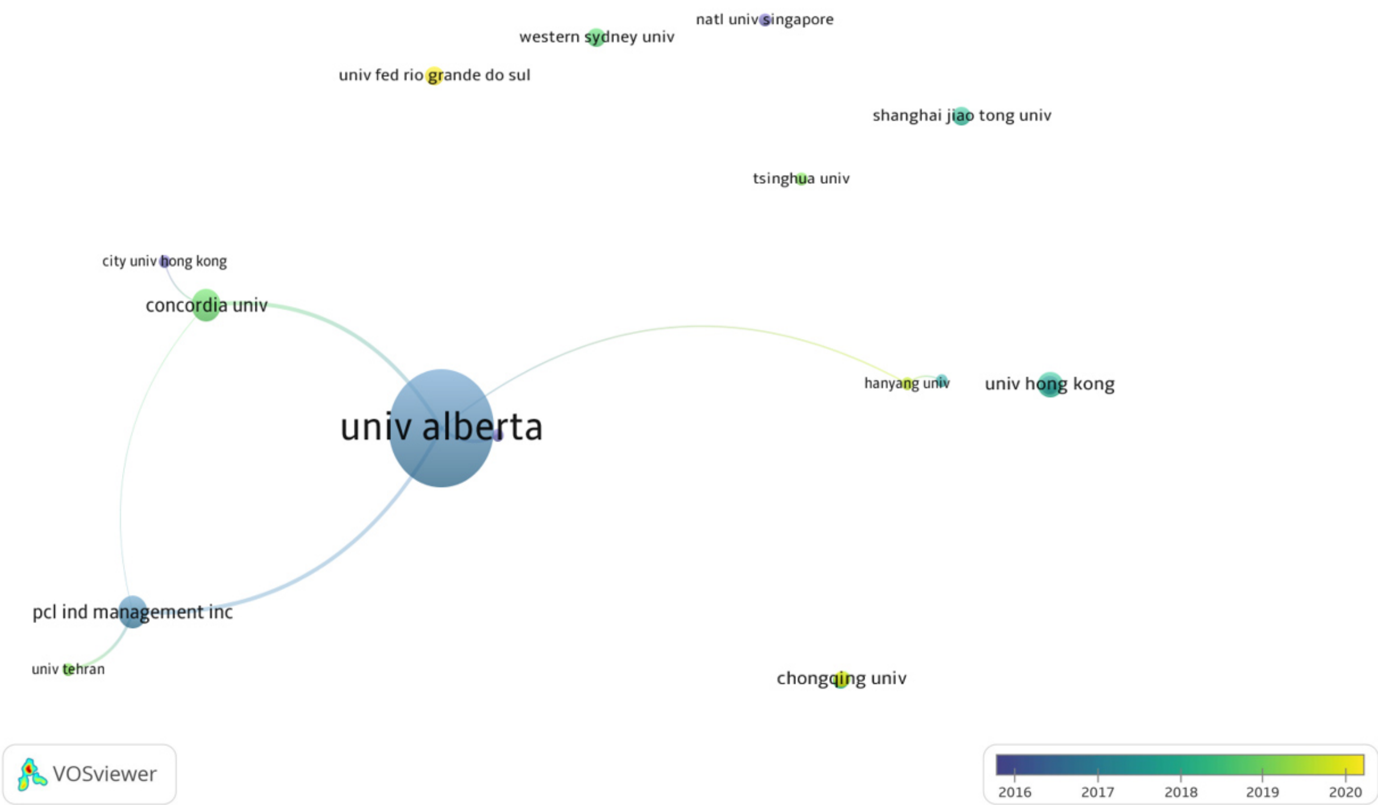


Figure 5: Network of pre-eminent institutions in MCR

Meanwhile, most of the key institutions identified in the previous 'general' review of MCR [12,39] are not active research hubs for DTT application in modular construction except Concordia University and the City University of Hong Kong. Hence, this reveals that most top institutions involved in MCR have little or no interest in applying DTT in modular construction. Although MiC originated from the USA, only an institution (Pennsylvania State University) in the country appears in the top-10 institutions with TA-MiC publications (Table 3). Moreover, based on citations and publications, the University of Alberta is the most influential in TA-MiC research. However, Shanghai Jiao Tong University in China, with an average normalized citation of 6.06, is significantly improving its contributions regarding the application of DTT to MCR. The key institutions highlighted in the generated network are unique in their contributions to the TA-MiC research area and can be regarded as key technology hubs for MCR.

Table 3: Quantitative analysis of the leading countries and institutions in MCR

Institutions/Countries	Documents	Citations	Avg. Pub. Year	Avg. Norm. Citations
Pre-eminent Institutions				
University of Alberta	18	183	2017	1.02
PCL Industrial Management Inc	5	49	2017	0.76
Concordia University	5	17	2019	0.55
University of Hong Kong	4	55	2018	0.83
Pennsylvania State University	3	63	2017	0.91
Shanghai Jiao Tong University	3	53	2018	6.06
Western Sydney University	3	48	2018	1.21
Universidade Federal do Rio Grande do Sul	3	17	2020	0.93
City University of Hong Kong	2	56	2011	0.98
Universiteit Twente	2	40	2012	1.36
Leading Countries				
Canada	25	199	2018	0.85
China	22	215	2018	1.39
United States	16	121	2015	1.51
Australia	9	102	2018	1.08
England	6	43	2018	0.84
South Korea	5	6	2019	0.20
Netherlands	3	41	2014	0.94
Brazil	3	17	2020	0.93
Iran	3	12	2019	0.78
Singapore	2	11	2017	0.37

3.2.1.3 Leading countries

The last phase for the mapping of the collaboration networks examined the contributions of countries to MCR. Scholars domiciled in twenty-four countries have published papers on TA-MiC. However, the collaboration network generated using the procedure in Appendix B reveals 23 countries – except for Scotland with 1 TA-MiC publication. The generated network (Figure 6) has nine links with a TLS of 19, of which only seven countries have a form of collaboration with each other. The most influential countries are Canada, China, and the United States (USA) within the collaboration network with more links and TLS of (5,9), (3,9), and (3,9), respectively. Canada is the most significant contributor to TA-MiC research. The strongest collaboration links in the network are between USA-China (TLS=4.00) and USA-Canada (TLS=4.50); the connection between the other countries is either non-existent or weak. The gaps in the links are a consequence of the lack of cross-region applications of DTT in MCR. Hence, there is a need to validate technologies applied within a country context in other regions.

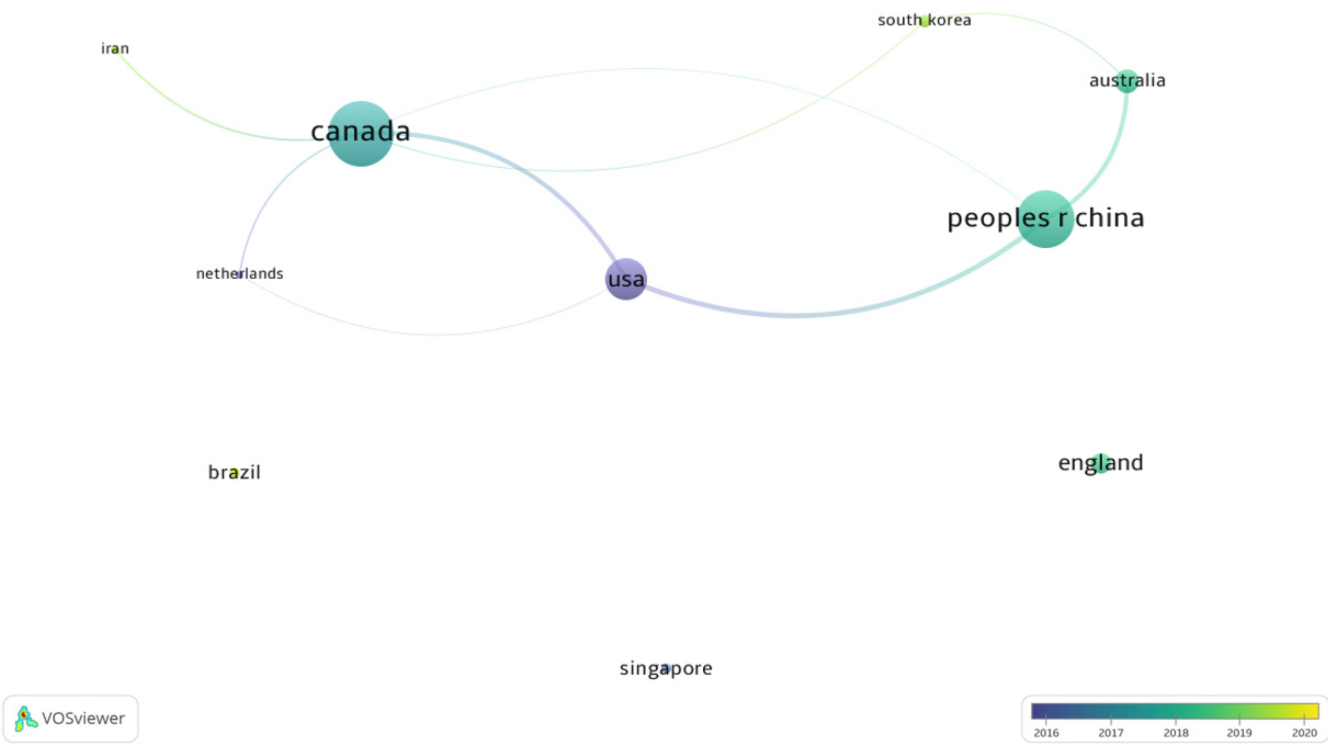


Figure 6: Network of leading countries in MCR

The top-5 ranked countries (Table 3) in this study are similar to previous ‘general’ MCR review studies by [12,13], although these countries change rank places. Two developing countries are represented in the network, with Iran maintaining a link with Canada and Brazil being isolated. Some of the barriers to MiC adoption in developing countries are highlighted by Wuni and Shen (2020). Citation-wise, research studies in China are the most cited, and those from Singapore have the least citations. However, based on the average normalized citations (*which cater to the fact that older documents have more time to gain citations*), studies in the USA are the most impactful among MiC researchers (Table 3). The countries with the latest entries of MCR publications are South Korea, Iran, and Brazil.

3.2.2 Mapping of the knowledge areas (*co-occurrence of keywords analysis*)

Keywords serve as reference points towards understanding the research field's contents [21] and outline the research domain boundaries and track the research field's evolution over time. The TA-MiC knowledge areas illustrated in Figure 7 show the structure, trend, and relationship among the various research topics in MCR. A total of 450 keywords were identified in the 82 indexed research corpus. The generated network has 147 links with a TLS of 93.50 and 22 keywords nodes – using the analysis process described in Appendix B. As stated by [14], the links between The salient research themes identified within the network are “simulation,” “building information modelling,” “management,” “optimization,” and “design,”; and their respective TLS are contained in Table 4.

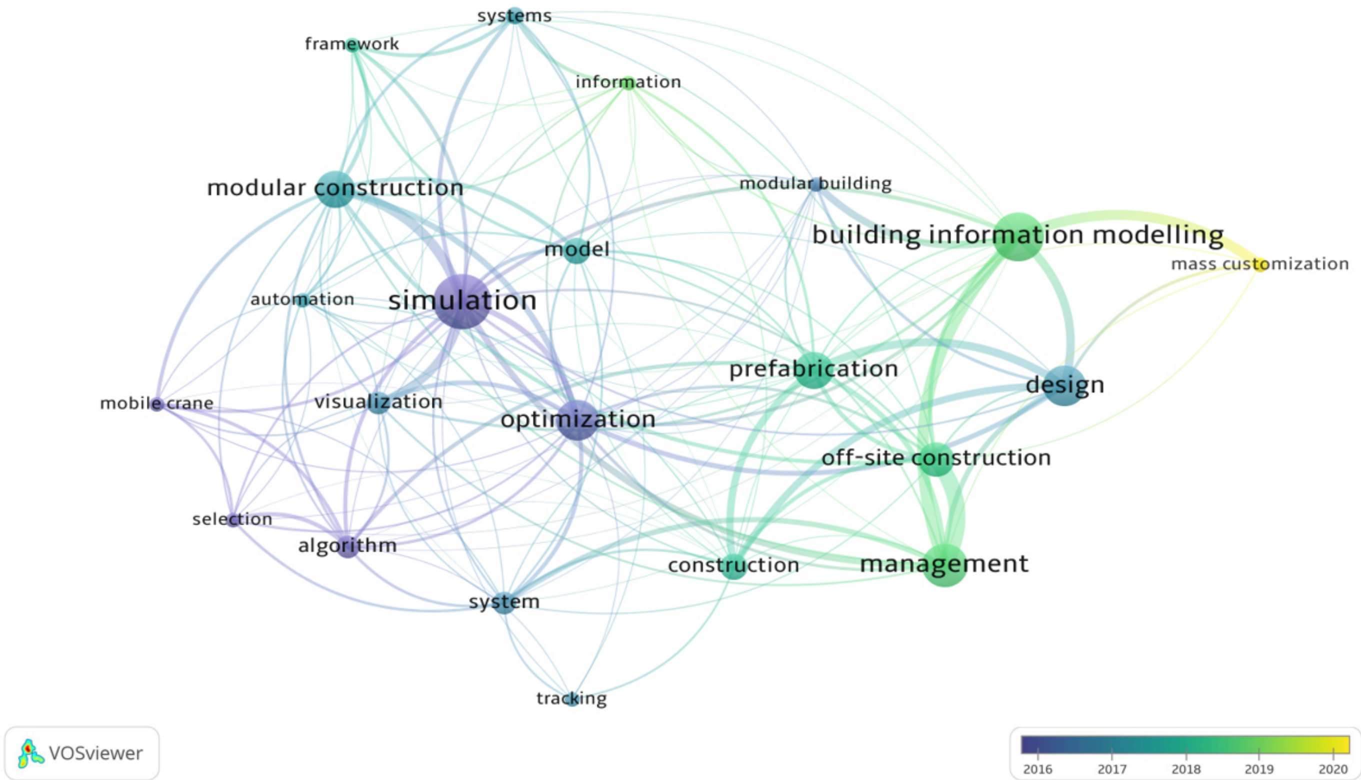


Figure 7: Network of salient MCR knowledge areas

Other interrelated keywords that mostly recur with these top knowledge areas are: (i) For "simulation," its pairing with "visualization" and "modular construction" has TLS of 2.18 and 2.41, respectively. (ii) For "BIM," its pairing with "design," "mass customization," and management with has TLS of 2.00, 2.50, and 2.78. (iii) For "management," its pairing with "simulation" and "off-site construction" has TLS of 1.53 and 3.83. (iv) "Optimization" pairing with "design" and "modular construction" with TLS of 1.25 and 1.46; and (v) "Design" pairing with "construction" and "prefabrication" with TLS of 1.75 and 2.00. The keywords pairing shows how these salient themes have influenced other research areas in the MCR domain. Knowledge domains such as "tracking," "optimization," "design," "algorithm," and "simulation" are the most cited and pivotal to MiC projects and the MCR community. The network visualization map revealed three main clusters with each of its subset's keywords representing related research themes, as shown in Table 4. Furthermore, these research areas and themes have significantly shaped the emerging and influential integration of DTT in modular construction concepts.

Table 4: Quantitative analysis of the MCR knowledge areas

Keywords	Cluster	Links	TLS	Occurrences	Avg. Pub. Year	Avg. Citation	Avg. Norm. Citations
Simulation	2	20	17	19	2015	12.3	1.03
Building Information Modelling	1	18	15	17	2019	7.5	0.76
Management	1	13	15	15	2019	9.7	1.66

Keywords	Cluster	Links	TLS	Occurrences	Avg. Pub. Year	Avg. Citation	Avg. Norm. Citations
Design	1	10	11	14	2017	14.6	1.1
Optimization	2	20	13	14	2016	15	1.04
Prefabrication	1	16	11	13	2018	8.3	1.84
Modular construction	3	15	12	13	2017	7.8	0.79
Off-site construction	1	12	11	12	2018	4.3	1.62
Construction	1	16	8	9	2018	8.1	0.62
Model	3	17	8	9	2018	10.4	1.15
Algorithm	2	14	8	8	2016	12.5	0.93
Visualization	2	14	8	8	2017	8.9	0.85
Systems	3	11	6	6	2017	10.2	0.89
Modular building	1	12	5	5	2017	11.2	0.96
Mass customization	1	5	4	5	2020	0.6	0.96
Tracking	2	6	2	5	2017	20.2	0.62
Mobile crane	2	10	5	5	2016	11.6	0.92
Selection	2	11	5	5	2016	11	0.81
Information	3	13	5	5	2019	10.6	0.91
Automation	3	15	5	5	2017	9.2	0.96
Framework	3	10	5	5	2018	9	0.9

3.2.3 Top cited MCR publications

A scientometric analysis of the direct citation received by MCR articles was also conducted as revealed in Table 5 and described in Appendix B, which contains 12 top TA-MiC related articles with at least 20 citations. The most cited paper is Yin et al. [9], which utilized RFID and personal digital assistants (PDAs) to manage and transmit the multifaceted MiC project information using the internet to the manager or relevant site personnel. Other studies that integrate RFID technologies include [41] that compare the effectiveness of a knowledge-based RFID system and a barcode-based system for a precast construction supply chain, resulting in over 60% savings in operational costs and reduces errors when RFID-based system is deployed. Also, Altaf et al. [42] deployed RFID along with a data-mining, simulation-based approach to managed MiC assemblies production.

BIM was integrated for MiC projects in [43] and [44] studies, where the former deployed Internet of Things (IoT) to develop smart construction objects for precast construction. In comparison, [45] and [46] advance genetic algorithms to optimize modular units' layouts. Simulation and automated systems for MiC projects were discussed by other well-cited articles [47–49]. However, comparing the citation metrics of documents published in older MCR articles with newer ones may not argue for a fair comparison. Hence, based on normalized citations as advised by [30], [50] received the highest normalized citation and is considered the most influential within the TA-MiC publications. These publications are fundamental bedrock for TA-MiC research. The relevant data provided can guide researchers and industry practitioners to identify key studies in MCR and how relevant DTT are applied in modular construction.

Table 5: Top cited MCR articles

Document	Title	Citations	Norm. Citations	DTT used
[9]	Developing a precast production management system using RFID technology	76	1.00	RFID, Personal Digital Assistants, wireless internet
[45]	Site precast yard layout arrangement through genetic algorithms	56	1.96	Genetic algorithms
[43]	Smart construction objects	41	1.00	BIM, IoT, IFC extensible markup language
[51]	Interlocking system for enhancing the integrity of multi-storey modular buildings	29	1.99	Modular Integrating System, Construction automation
[47]	Automated post-simulation visualization of modular building production assembly line	29	1.98	Simulation and visualization system
[44]	Design for manufacture and assembly-oriented parametric design of prefabricated buildings	28	1.92	BIM
[48]	Simulation-based multiagent approach for scheduling modular construction	24	1.78	Simulation-based auction protocol, Scheduling applications
[50]	Autonomous production tracking for augmenting output in off-site construction	23	2.13	Automated production tracking system
[46]	Improved precast production-scheduling model considering the whole supply chain	22	1.89	Genetic algorithms
[41]	RFID enabled knowledge-based precast construction supply chain	22	1.89	Knowledge-based RFID system, barcode system
[49]	Neuromodex - neural-network system for modular construction decision-making	21	1.45	Trained neural network system
[42]	Integrated production planning and control system for a panelized home prefabrication facility using simulation and RFID	21	1.44	RFID, optimization algorithm, simulation

3.2.4 Scientific mapping of the key MCR sources

The 82 indexed bibliographic records are sourced from 26 journals, while only five journals have at least four records within the dataset. The scientometric analysis for the top MCR sources described in Appendix B results in a generated network (Figure 8) of 14 links and a TLS of 33. The three authoritative journals where MCR researchers publish their research findings are *Automation in Construction*, *Journal of Computing in Civil Engineering*, and *Journal of Construction Engineering and Management* with a minimum TLS of 10; and constitutes 28%, 13.41%, and 7.32% of MCR publications in the dataset. However, *Automation in Construction* is the most prominent journal for MCR based on the analytic metrics indicated in Table 6 with 23 publications, TLS of 24, citation counts of 386, and a very high normalized citation metric (44.8).

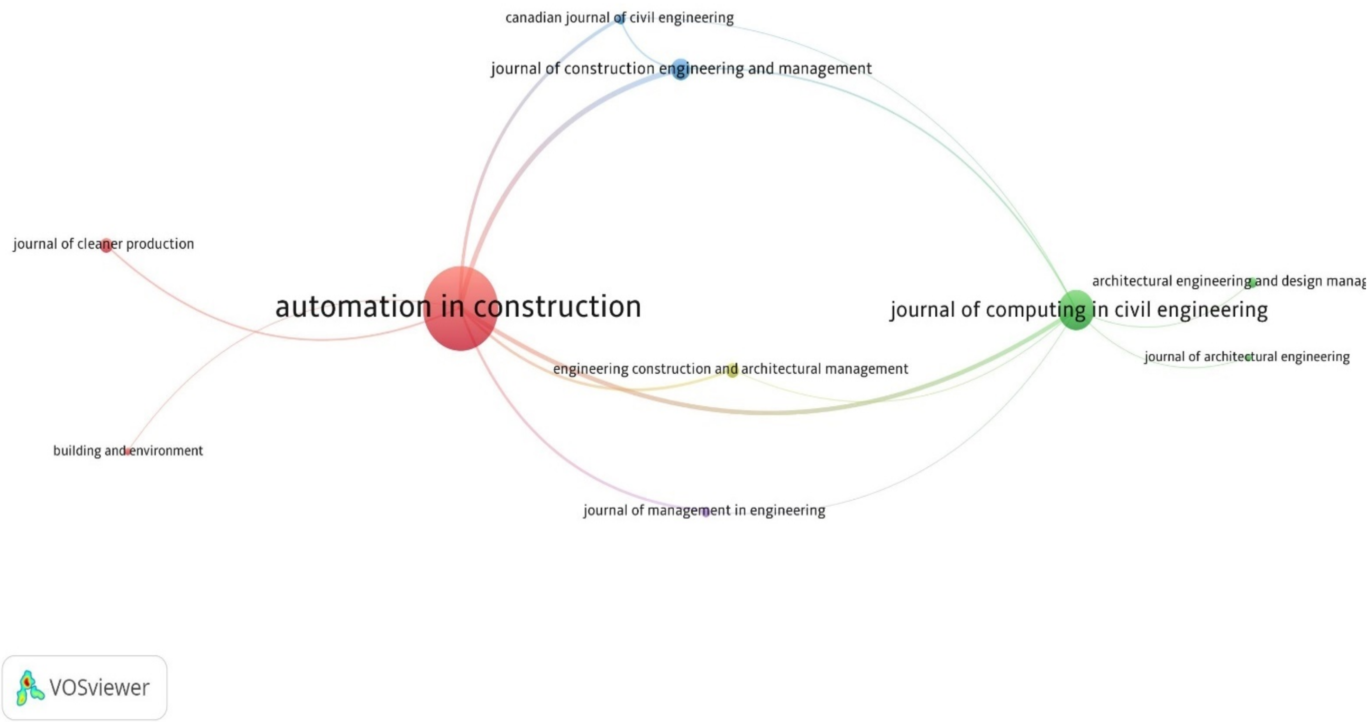


Figure 8: Network of key MCR publication sources

Also, in the rank of influential publishing outlets that serve as links between various MCR outlets are the Journal of Computing in Civil Engineering (0.869), Journal of Cleaner Production (0.866), and Journal of Architectural Engineering (0.834) based on the average normalized citations. Table 6 shows the impact factors of the top-cited journals based on the WoS database. The generated network also revealed close links between these key journals, and they can be considered scholarly hubs for MCR-related publications. Hence, these top MCR sources are recommended for researchers, policymakers, and industry practitioners interested in modular construction to follow.

Table 6: Key MCR publication sources

MCR Publication Sources	Counts	Citations	Norm. Citation	Avg. Pub. Year	Avg. Norm. Citation	Impact factor	%
Automation in Construction	23	386	44.8	2017	1.95	5.669	28.05
Journal of Computing in Civil Engineering	11	144	9.6	2014	0.87	2.979	13.41
Journal of Construction Engineering and Management	6	31	2.2	2018	0.37	2.347	7.32
Journal of Cleaner Production	4	21	3.5	2019	0.87	7.246	4.88
Engineering Construction and Architectural Management	4	3	0.2	2020	0.05	2.16	4.88
Canadian Journal of Civil Engineering	3	24	2.0	2016	0.65	0.985	3.66
Journal of Management in Engineering	3	21	2.5	2018	0.82	2.867	3.66
Architectural Engineering and Design Management	3	13	1.0	2018	0.33	**	3.66
Building and Environment	2	18	1.6	1994	0.78	4.971	2.44
Journal of Architectural Engineering	2	2	1.7	2019	0.83	**	2.44

Note: ***Emerging Sources Citation Index - Web of Science; % - Percentage*

4. Systematic analysis

In this section, the DTT employed for modular construction is analysed using a systematic technique to understand the breadth and depth of its application for MiC projects. The relative strength (benefits) and limitations of each DTT in relation to its application in MCR are also highlighted. The DTT applications in MCR are categorized and discussed based on the MiC project phase that they were applied. There are three main phases in MiC projects [1], which are the offsite prefabricated manufacturing phase, prefabricated transportation (PB) phase, and the onsite assembly (OA) phase. The 82 bibliographic records – of which 43 articles were carefully selected and reviewed and the relevant DTT applications in the research corpus are presented in the following sub-sections. Figure 9 illustrates the frequency of applying the DTT across the MiC project phases, as evident from the indexed WoS research corpus (82 articles). Overlaps between the three main sub-sections existed and were settled based on the predominance of how DTT was applied to a MiC phase in each article or based on the core focus of that article.

4.1 Phase 1 – Offsite prefabricated manufacturing

The offsite prefabricated manufacturing (OPM) phase of MiC projects generally occurs almost concurrently with the onsite assembly phase [52]. It is a critical phase – as this is where the precast modules are produced and necessary structural, architectural, and sustainability designs and criteria are embedded in the prefab modules. In one of the earliest applications of DTT in modular construction at the offsite prefab phase, [53] built a computer-based capacity planning and simulation model to assist managers in assessing and forecasting the market and plant utilization. The simulation model uses the demand and shift patterns to estimate the precast plant performance. More so, at the concept and planning stages of a construction project, many decisions need to be made, one of which includes the method of construction – a stick-built or modular construction? With this in mind, [49] proposed Neuromodex. This system utilizes neural networks to help clients, project teams, and contractors decide if MiC is the best approach for the project endeavour. The neural network system uses five criteria [49] to help the practitioners reach a feasible decision.

A key benefit of modular construction is the quality of the construction product or modules. To address quality issues involved in the OPM processes, [54] developed a visualization system using project-based augmented reality (AR) technology. The novel AR-based system permits the user to peruse vital design information of the module being manufactured and make relevant cognitive assessments on the product quality. However, the developed system is still immature and was applied on a smaller scale. Similar technology could be extended to the OA phase for quality control processes and material handling.

Meanwhile, to facilitate the inspection of modular units within the controlled factory environments, [55] developed a vision-based system coded using Python, which extracts relevant data from an industrial camera. The extracted data is then compared with the BIM model manufacturing data for each module unit. [55] examined its practicability for the prefabrication of light-gauge steel frames, which provides evidence of its accuracy.

Moreover, RFID technology adoption is increasing in the construction industry, especially for modular construction methods. For instance, [42] employed an RFID system to automate production data collection in a prefabrication facility. Using a simulation model integrated with an optimization algorithm, a RANSAC model was developed [42]. The RANSAC model helps clean the generated RFID data, which is useful in developing a discrete event simulation (DES) model to enable construction managers to visualize the assembly line production and optimize the production schedule in the offsite manufacturing of panelized walls. Yin et al. [9] also used RFID integrated with Personal Digital Assistants (PDA) for various quality inspections – such as production process, materials, molds, and managerial inspections. Using RFID and PDA minimize information losses comprehensively. Hence, in the OA phase, information on the PDA can be shared in real-time to ensure speedy assembly.

Meanwhile, [56] developed a GBMH algorithm using the control theory concept to monitor, detect, and correct possible variations in the desired performance level of offsite prefab factories. The system was implemented in a structural steel prefab facility at a minimum cost to the project [56], which helped the prefab facility manager predict the prefab shop's production performance. Other benefits are that MiC projects can be delivered on schedule, avoiding penalties due to delay and reduced overhead costs. Furthermore, [50] developed a production tracking and control system for a large-scale prefab plant in Australia to resolve deficiencies usually encountered in offsite construction works. The development system could detect any potential shortfalls in production against the predefined targets and make the necessary adjustment to the project capacity parameters and avoid escalating the costs due to the schedule delay.

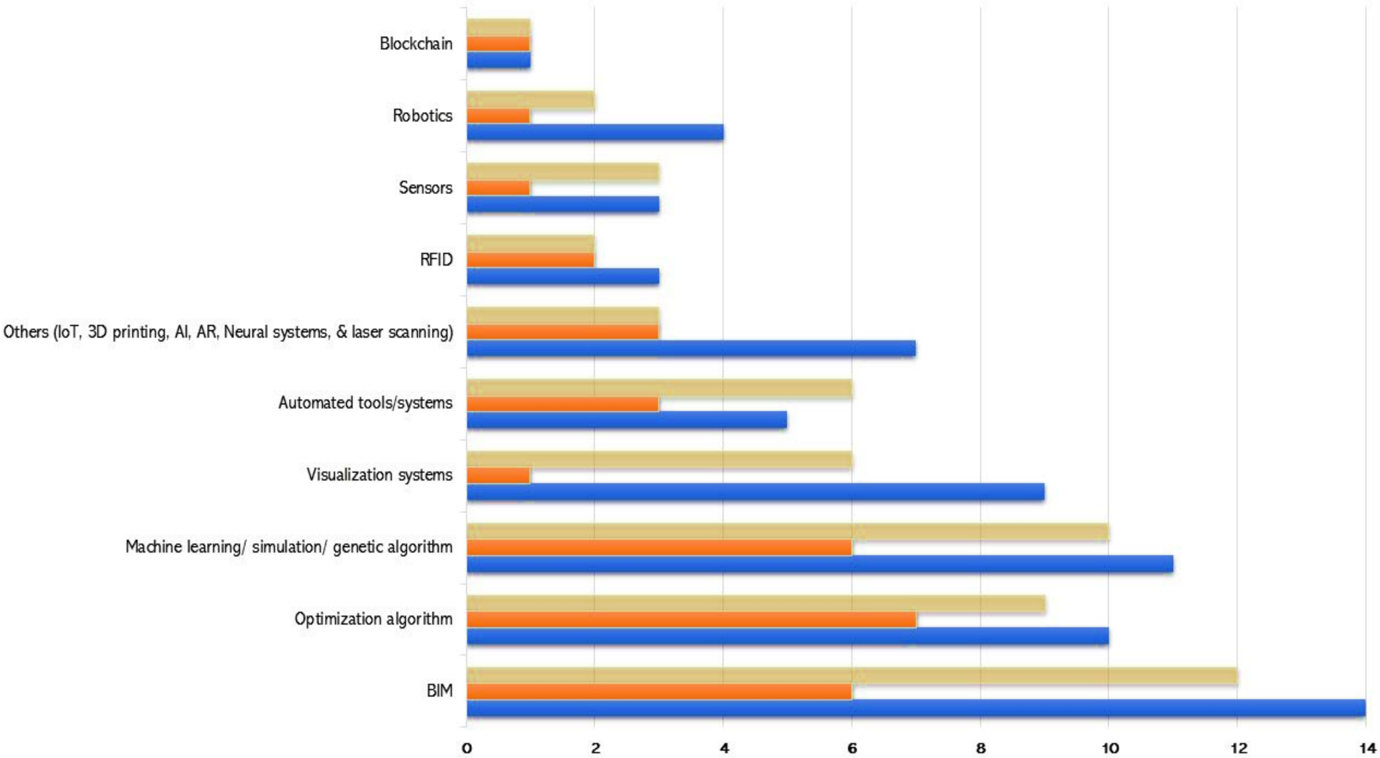
Each module manufactured in a prefabrication factory is a project on its own with associated activities and constraints. Hence, developing a feasible schedule for such large-scale and multi-unit projects and allocating project resources is a more daunting task. To this end, [48] developed a simulation-based auction protocol effective in resource levelling and scheduling of MiC projects even with limited data. The developed tools show better capabilities than commercially available software such as Microsoft Project and Primavera. Moreover, [57] implemented a scheduling optimization model to cater to an often neglected material logistics dynamics in construction planning. The advent of OPM has introduced some complexity to the supply chain management because of the necessity to deliver materials to the prefab manufacturing site. Thus, material management is of great importance to the supply chain of goods been delivered to the site (either prefab or onsite). The optimization model solves multiple constraint problems through proper representation as a constraint satisfaction problem [57]. It employs symmetrical search problems to determine an objective function that would locate and optimize such tasks such that the materials will be scheduled to the prefab manufacturing site in record time without conflicts in scheduling and minimize waste.

Moving to BIM-related DTT and use of artificial intelligence (AI) at the OPM phase. The most prolific author in the TA-Mic research field, Al-Hussein Mohamed, co-authored two articles where BIM was used to verify the intersections of steel and wood frame assemblies. In the first paper, [58] extended the use of 3D applications such as BIM to verify the manufacturability of steel frame assemblies automatically. The machine eligibility determination system (MEDS) helps detect the regions of intersection in steel frames and determine the areas requiring, for instance, the fastening of screws. However, the MEDS is limited by the computational time needed to detect the steel frame intersections. Also, the system cannot detect the contact area between the steel frame and other building elements. Secondly, using a similar BIM-based framework, [59] verified the intersections of two wood-frame assemblies and calculated the manufacturing locations as well. The MEDS system's functionality can be further developed to extend its use to more building elements and assist, especially in the placement of modules using cranes on the MiC building site.

DfMA technologies provide a lasting and comprehensive solution to the problems created when non-prefabricated buildings are adapted and fitted into fabricated structures. [44] implemented the DfMA integrated with the BIM model to aid the concept and development of DfMA-based parametric designs. Design and manufacturing are simple with DfMA, and it also provides an improved quality design. Its ability to save time and, at the same time, being cost-intensive makes it very attractive. Moreover, Baghdadi et al. [60] utilized AI to enhance the design collaboration between the engineer and architect to achieve optimal beam and wall layout for the building as well as facilitate easy fabrication of the building elements. However, it may not be feasible for practical usages, as the AI system would require 149 iterations [60]. The building plan's complexity can also add to the difficulties of applying the algorithms for optimum wall configurations.

The ergonomic posture of workers is critical to improving their safety and productivity and indirectly reducing project costs. In this view, [61] advanced a monocular vision-based system that utilizes videos from a camera to track the construction workers' postures and motions in a modular workshop. However, the system needs improvement to cater to workers' deep squat postures and for uncontrolled environments such as the construction site. Meanwhile, [62] integrated 3D visualization technologies to develop ErgoSystem, which provides an automated way of assessing the ergonomic risks of different work methods. ErgoSystem, when demonstrated in practice, shows significant advantages over the conventional means [62]. It also eliminates the need for costly devices to assess works ergonomic risks on the project site and is less time-consuming. However, the system does not analyse workers' productivity based on the different work methods; and combines head and neck flexion for risk assessment instead of separately.

In summary, the need to improve the BIM model to include relevant manufacturing information of construction products, especially steel and wood frame assemblies, cannot be overemphasized to enhance the current BIM systems used in modular construction. More so, the feedback or data provided by the adopted system or DTT on each module unit being fabricated can easily be extracted and stored in the blockchain system for clients, architects, engineers, and managers' future use and analysis. This data on the BCT network can be used for future modification and improvement of the existing technological system.



	BIM	Optimization algorithm	Machine learning/ simulation/ genetic algorithm	Visualization systems	Automated tools/systems	Others (IoT, 3D printing, AI, AR, Neural systems, & laser scanning)	RFID	Sensors	Robotics	Blockchain
OA Phase	12	9	10	6	6	3	2	3	2	1
PB Phase	6	7	6	1	3	3	2	1	1	1
OPM Phase	14	10	11	9	5	7	3	3	4	1

Figure 9: Frequency of application of the DTT across the different phases of MiC projects in MCR

Data source: WoS Database

4.2 Phase 2 – Prefabricated transportation

The prefabricated transportation phase is the least critical. Still, it serves as a unique linkage between the other two MiC project phases. However, any difficulty or low efficiency of operationalization at this phase could potentially disrupt the logistics and scheduling of the onsite assembling of the MiC modules with attendant risks and costs to the involved project stakeholders. A key performance challenge of MiC projects is concerned with the logistics operations of prefab modules between the prefab factory and the project site. Hence, to improve the freight operations, [63] developed the Route Guidance System (RGS) based on a traffic simulation model. A unique aspect of the RGS is that it embeds the driver's behavioural components and the prefab modules' information supply strategies. The RGS can also predict traffic for RGS-/unequipped trucks and shows a better performance than the existing static systems in terms of the equipped truck emissions and fuel consumption, total travel time, and miles, among others [63]. However, the system does not factor in the impact of the public traffic control system. It cannot also cull real-time traffic information, which is a major let-down for its everyday implementation.

Moreover, using scenario analysis, [64] explored the potentiality of adopting automated guided vehicle (AGV) technology for logistics. The article reckoned that when fully developed, AVG would improve efficiency and productivity for module transportation. However, good synergy between AVG and other modern technologies will help to fully achieve logistics automation. Meanwhile, in the transportation of the precast modules, especially via the road networks, they are often subjected to various road conditions (*such as road roughness and speed, acceleration direction*), leading to damages to the modules when delivered to the building site. [65] used tri-axle accelerometers and GPS trackers to collect transportation data of precast modules, which are analysed using power spectral density. The integrated system provides a mechanism to measure the mechanical responses of the precast modules during this MiC phase.

To solve problems related to the prefabricated modules supply chain, [66] developed a PSO algorithm based on the just-in-time (JIT) principle. The PSO algorithm is also beneficial for contractors and suppliers to produce their bids for MiC projects [66] and coordinate the interfaces between the project stages and the stakeholders. However, the PSO model does not consider other significant issues like supply delay or disruption in transport routes and means. Using a genetic algorithm, [46] modified the traditional precast scheduling model to integrate its transportation processes, which improved the delivery of the precast components to the construction site. The improved scheduling model also helped achieve significant cost savings of at least 17.7% for daytime delivery and a higher savings of 35.7% for night-time module transportation. However, the scheduling model does not consider the delivery trucks or other resources' capacity or inefficiency. Also, such savings in night-time delivery might not be practical on construction sites in the neighbourhood of residential buildings.

In summary, technologies such as BIM, RFID, AI, computer-based vision system, blockchain and the like must be systematically integrated to provide intelligent and real-time assessment, monitoring, and management of the supply chain and transportation of the prefabricated modules.

4.3 Phase 3 – Onsite assembly

The onsite assembly phase culminates the whole modular construction process. The arriving MiC modules are inspected; any module faults are repaired and hoisted on a crane for proper placement on the building site. These managerial processes and others – such as valuation, quality control – generate many data that can be better managed using relevant DTT such as BIM, laser scanners, and other tools. BIM technologies are one of the most frequently used technologies for the MiC OA phase. For instance, due to the increasing complexity in engineer-to-order (ETO) modules as a result of the overlaps in resources and project stages, ambiguity in client demands, and the like, [67] proposed a site logistics planning and control system which utilizes a 4D BIM plus lean production principles.

The implemented system increased productivity and reduced hours spent transporting the modules to the site and the distance covered onsite in assembling the modules. However, the BIM system is limited because it uses a simple BIM model for managing the shipment of steel frames to the project site. More so, [68] developed a BIM-OfA assessment system that integrates lean principles and DfMA to optimize designs and assemblage of modular buildings. The system relies on BIM for efficient information processing for better decision-making. The BIM-OfA system is also useful for the users in the selection of construction materials and methods. However, it is only suitable for building envelopes and not for other building elements.

Moreover, workplace conflicts are common due to clashes between labour crews installing the precast assemblies on the building site. These conflicts can negatively affect workers' productivity and safety. To attenuate this, [69] proposed a 4D BIM-based tool to identify and eliminate potential workplace conflicts during onsite prefab installations. However, for practical purposes and user-friendliness, the tool's algorithms need improvement as the Revit-based tool's runtime is long. Meanwhile, [70] extended BIM techniques and strain sensors for precast modules' structural health monitoring. The proposed system can detect and visualize any deformation in precast building components and any vibration or strain [70]. It helps expose modules that might have hidden or visible damage either during transportation or during the manufacturing phase.

More so, moving to 3D laser scanning technologies, this DTT was employed by [71] to examine and inspect the geometric qualities of prefabricated mechanical, electrical, and plumbing (MEP) modules. The scanned data is compared with the designed module's BIM model. The experimental usage of this DTT shows it saves time and is more accurate than the manual inspection process and can improve the productivity of the inspection foreman. These benefits are very significant to project success as reworks of MEP modules on the project site is about 20 per cent [72], of which 10% relates to quality issues [73,74]. Also, the bulkiness of precast modules and heavy machinery on the project site, coupled with other resources, usually presents a big challenge for site management. Hence, [45] employed genetic algorithms (GA) model on a case study project, which helped achieve an optimal layout arrangement for precast site yard at a reduced cost for resource flow. The GA-based model application can be extended to solve layout problems in precast production factories and warehousing.

Key equipment used in hoisting and installing the heavy precast components on the project site is mobile and tower cranes. Due to the type of tasks to which these cranes are employed and to save time and cost in installing the module and enhancing site safety, there is a need for proper planning and configurations of the crane positions' layout. To this end, a number of TA-MiC studies explored and implemented some DTT to analyse the best positioning for cranes. For instance, [75] developed an automated crane planning and optimization system that uses numerical algorithms and the HeviLift software suite to precisely determine the feasible crane locations. Meanwhile, Shahnavaz et al. (2020) connected the 4D lift animation plugin with BIM to simulate and define multi-mobile crane paths.

Other related studies [77,78] also employed similar DTT. However, the technological system developed by [75] does not support tower cranes or two-crane lift layout configurations. In contrast, the BIM-based lift system [76] cannot automatically define the mobile crane layouts. Hence the user must manually input the lift path, which is more tasking. Finding technological synergies between the DTT developed in these studies can give a more intelligent and automated system for crane planning and optimization for diverse crane systems.

In another context, the need to examine the performance of installed prefabricated modules in high seismic regions led [79] to develop a seismic force-resisting system (SFRS). The SFRS was implemented for a timber-based modular construction, which reduced the seismic-induced force and provided a cost-effective method for resilient modular timber buildings. The re-centring system [79] can also be used for other structural systems using a different material.

[80] employed wind field simulation and numerical analysis to estimate the performance of the wind-induced MiC projects embedded with concrete cores in coastal regions. High-level winds like typhoons are serious threats to modular steel construction. The developed system improves beam and column joints stiffness and energy dissipation performance.

Also, multi-storey modular buildings require adequate design to maintain their structural integrity against severe loading conditions. The joints and connections between these precast modular units are crucial to the structural integrity of modular buildings. Towards this end, [51] advanced an interlocking system to improve modular buildings' integrity based on the design requirements. The system facilitates an automated assemblage of the precast components and manages the structural tolerance. It provides a greater solution as compared to the traditional non-automated connection methods. These components are added so that the geometric features become more flexible than conventional fasteners. They are also suitable for rapid and automated assembly.

4.4 All MiC phases

Articles that do not fall precisely under any of the three MiC phases but cut across all the phases are presented here. For instance, using a case study of a MiC project in Italy, [81] presented how the early adoption of BIM on the project can facilitate information workflow among the downstream and upstream players. The study also highlighted how the stakeholders' inputs and requirements were merged to facilitate the project [81]. The upstream aspect of modular construction refers to the critical stages where the concept, design, and material inputs required for the MiC project are appraised and formulated. Meanwhile, the downstream is the opposite end, where the MiC project is procured, unit modules are produced, transported, and installed on the building site.

Bataglin et al. [82] produced a 4D BIM model to link the 3D BIM model and the MiC production plan to improve the project's performance by removing uncertainty in the assembly process and non-value-adding activities. The article also presented how this enhanced BIM system helped implement lean production by updating the 4D model with logistics decisions and providing data on the fabrication and assembly process in an ETO environment. However, the BIM system was only experimented on a single prefabricated module with a short lead time. It did not assess the impacts of delays in determining the cost-benefits of implementing the BIM system. Also, [83] explored the IFC-based information systems in the construction industry for interoperability and tested their reliability for a precast concrete project. The article stressed that the absence of a typical BIM data exchange limits information processing in MiC projects and among the fragmented professional services.

The construction industry's logistics system has significantly changed since the gradual shifts from stick-built construction to modular construction. Hence, there is a need for the industry to reinvent the supply chains of MiC projects, which led [84] to develop an optimization logistics model for MiC projects – which covers all the tiers of its operations. The stochastic model captured demand and schedule variations and helped practitioners make informed decisions for the MiC projects' logistics. [85] also integrated various technologies such as sensors, BIM, and virtual construction management platforms to conduct a continuous quality inspection on precast building components. These integrated tools can be applied efficiently across the MiC project lifecycle.

In summary, from the literature, there are no process framework or execution strategies on how BIM or any other DTT can be implemented across the MiC project stages – *from project brief to post-completion* – and the relevant data required for its successful application. The future development of such DTT execution strategies should capture the various stakeholders' roles and engagement in the MiC supply chain.

5. Potentiality of integrating blockchain and DTT in MiC projects

Blockchain technology application has been on the rise for about a decade, and it brings enormous possibilities to virtually all aspects of the economy. Generally, the construction industry is a latecomer in adopting innovative technologies [86]. Hence, this does typically affect the learning curve of applying BCT to construction processes by practitioners. However, the construction industry stands to enjoy the latecomer advantages such as lower cost of entry, a more mature BCT, and fewer market uncertainty issues [87] later on.

The deployment of blockchain also provides a better prospect as a new collaborative system than BIM, which has been plagued by the issues of interoperability, portability, and lack of uniform standards [88,89]. Recent improvement in BCT architecture provides avenues of enhancing BIM and other DTT towards further embedding these tools for full or partial deployment in construction projects, especially for MiC projects. The developing synergy between BCT, DTT tools, and other IoT devices would practically bring enormous potentials and automation to MiC projects. Some of the potential benefits and risks that may likely spring up from these massive digital integrations are discussed in the extant literature [90–92]. As seen in Section 4, several DTT have introduced many possibilities to MiC projects. Still, it is expected that its integration with blockchain and other IoT devices will lead to the development and deployment of a 'single' viable technology. Also, this will help fully digitalize and automate MiC processes and overall sustenance of the MiC projects, thus providing a greater output.

BCT is a distributed ledger technology in which transactions are cryptographically chained into growing blocks [87] and secured on a peer-to-peer type system [86]. The BCT offers a considerable capacity to the construction industry, from transparency to smart contracts, increased trust, prompt settlement of contractual obligations, and the like. The BCT and DTT blend is expected to revolutionize MiC projects at prefab manufacturing, prefab transportation, and/or the onsite assembly phase. To conserve space, we briefly summarize the potentiality and benefits of integrating BCT and four key DTT in MiC projects (these may be applicable for other construction projects).

5.1 Blockchain integrated with BIM for MiC projects

The advent of BIM has improved efficiency across the construction industry as building data can be mapped out, modelled, and structured even before construction starts, and changes can be made during construction. Moreover, integrating blockchain with BIM will further improve the information sharing process and promote transparency among project stakeholders. Blockchain has an emerging ICT, provides the industry, especially in construction projects (such as MiC), with a standard of framework and protocol to facilitate collaboration and sharing of BIM data from multiple project stakeholders [93]. Currently, the industry is faced with an "*islands of information"* problem where data are fragmented [93]. With BIM and blockchain integration, such problems are avoided, and there is increased communication and information sharing [94]. As materials move from the prefab manufacturing phase to the onsite assembly, relevant information can be accessed about operations in a decentralized way that gives all parties confidence. Changes can be made on the BIM model of the MiC projects, and will blockchain deployed in such project, it can be accessible to relevant project stakeholders with ease. Also, relevant transactions and verification in MiC projects can be carried out quickly because smart contracts can be used [95].

5.2 Blockchain with machine learning and genetic algorithms

Machine learning and genetic algorithms provide an optimal solution in every aspect of science due to the data available to train models effectively, and both make use of historical data [96,97]. The model is trained with labelled data [96,97] in a supervised learning algorithm, while unsupervised learning employs unlabelled data. Combining BCT with machine learning (ML) and genetic algorithm (GA) would enable trained data to be fully decentralized and subsequently improve MiC processes performance. A study by Jamil et al. [97], who developed an intelligent blockchain-based platform, provides evidence that the integration of BCT, machine learning, and/or genetic algorithms can help in providing predictive analytics for MiC projects. These predictive analytics can be in the form of scheduling [97] of prefab production, assembling, and transportation; real-time control, logging, and monitoring of project milestones; resource utilization [97], among others. Errors in design and construction are largely minimized because of these predictive models. Quality designs can also be implemented with the introduction of machine learning. The model can learn through data from blockchain technology.

Data used for such predictive modelling based on ML/GA techniques are historical data [96–98] from similar MiC/other construction projects. Such data might be data generated from BIM models, building energy simulations, productivity, traffic congestion data, and the like. For example, in the transport phase of the MiC, predictive models can be developed to determine the exact time prefabricated materials will arrive on site. Machine learning algorithms provide a unique way of uncovering hidden patterns from large datasets [99–101]. Machine learning working with big data can build very accurate predictive models for the enhancement of the construction industry. Machine learning-enabled blockchain uses data collected through user experiences and behaviours to develop industry-based predictive models. Machine learning can be used to ensure production, transparency, security, and compliance checks. Instead of planning fixed scheduling activities from the prefab manufacturing phase to the assembling phase, Machine learning algorithms are being used to create flexible plans at the precise times they should happen. This reduces any form of uncertainty during the construction process. Quality control and product testing of prefabricated materials have become increasingly automated, with adaptive and computer vision algorithms being used to detect good and faulty products. This is possible only because expansive data is being used to train the machine learning predictive models.

More so, according to Miglani and Kumar [98], embedding ML with BCT can resolve data acquisition problems as blockchain can serve as a 'pipeline' towards which ML/GA algorithms can be fed with reliable and accurate data. Such results generated can be trusted by the stakeholders without the attendant security issues of centralized systems. ML/GA algorithms supported by BCT yields better predictive models, safer and tamper-proof data, increased stakeholders' confidence in the data (due to BCT's transparency feature). Thus, the BCT-ML/GA combination can provide an excellent boost for MiC projects. Combining data from the ML algorithm with those extracted from the BIM model would allow for better optimization of designs and the prefabrication – and with blockchain as the data hub, relevant process performances can easily be monitored and evaluated.

5.3 Blockchain with RFID technology

RFID has been employed in MiC projects to automate the collection of production data in prefabrication facilities [9,42]. RFID provides a trusted service application for stakeholders across the MiC projects' phases when embedded with the blockchain system. With an RFID-blockchain based application user interface (API), users can build customizable apps for varieties of processes or tasks involved in a MiC project using standard BCT protocols and mechanisms. This allows a decentralized generalized approach to construction with huge transparency with RFID data. A typical example is the case of smart contracts. In executing a smart contract, there is a need to know if a prefabricated building component has arrived on a location or if the required amounts of a meta beam have been brought in. This information can be fed in with RFID technologies. Modular construction with blockchain also provides security and data encryption. The encryption mechanism ensures security for data extracted from the RFID.

According to Lanko et al. [102], RFID tags can be put on construction materials or a prefab to monitor the various stages of its production, transportation, and its installation on the project site. Using RFID scanners which uses radio signals, data stored in these tags can be read, broadcasted, and stored on the blockchain as a record. Hence, it allows for automated data collection, which could be useful in logging project milestones. Other relevant data may be written or recorded as notes to include information such as the time, supplier, specifications of the material/modules, and digital signatures [103–105]. RFID tags can store data, so their use could be extended to identify and track construction products [106]. Therefore, a blockchain system that embeds RFID facilitate transparency across the supply chain, preventing issues like counterfeit materials, poor quality modules, poor storage conditions, unsuitable transport route, and the like. This is achievable when corresponding data in the RFID tag is stored within the blockchain [106].

5.4 Blockchain with optimization algorithms

Optimization algorithms have been widely adopted in MiC projects [42,57,75,84], and they have been very useful. Optimization algorithms like PSO, backward propagation algorithm, and k-means optimization employed a large amount of trained data to achieve high efficiency in the three phases of the MiC projects. Integrating blockchain with optimization would effectively provide a way for optimization to be achieved through the best routes. More so, according to Priyanka and Thangavel [107], implementing ML with optimization algorithms can assist with data mining for better predictive analysis of MiC processes. Blockchain systems are decentralized, and data is accessible in an open and transparent way to achieve the best solution at any phase in the MiC projects. Several studies [108–110] provide evidence of the feasibility of using BCT and optimization algorithms to predict and optimize MiC processes.

Summarily, to implement BCT-integrated DTT and IoT devices, the project team and other stakeholders must understand the fundamental purposes of adopting it. For instance, if no project or module unit data needs to be stored, BCT will not add additional technological value to the project from the data management angle. However, for a project with several mistrusting parties contributing to the project and in which their influences and actions can bear a lot on the project outcome, BCT will be a feasible and workable solution.

6. Conclusions

This study investigates the current state of research and practice in modular construction by examining the various digital tools and technologies applied in MCR to automate and digitalize the MiC process. The MiC itself is a technological derivative of the DfMA technique. Although some studies have conducted reviews on modular construction, this is the first study that critically examines and explores the application of DTT in MiC projects. The study conducted in-depth analyses to achieve the defined research objectives via the use of various research approaches such as data curation, science mapping (scientometric analysis), and systematic analyses.

An analysis of the research corpus and findings shows that MCR has gained increased interest among researchers and practitioners, most notably in the last decade than in previous years. Although the first paper on modular construction was published in 1970, the first published DTT application in MCR was in 1992. Currently, only about 18 per cent of studies in modular construction practically implemented DTT. Meanwhile, more than 70% of these TA-MiC articles are produced by only five countries – Canada, China, the USA, Australia, and England. The study also identifies the key research clusters and communities, which are those of Mohamed Al-Hussein, Taghaddos Hosein, and Hermann Ulrich. The most influential outlets for MCR articles are *Automation in Construction* and the *Journal of Computing in Civil Engineering* which topped the table in both publications and citations. Meanwhile, for the top-12 cited MCR articles, the prevalent DTT employed in these studies are simulation-based algorithms, RFID, BIM, and visualization systems applied mainly to either the offsite prefab manufacturing or onsite assembly phases of MiC projects.

The science mapping of the research themes in MCR revealed that the design and product-focused knowledge areas – such as *BIM, simulation, optimization, and prefabrication* – dominate. Meanwhile, management-related areas such as *offsite construction, modelling, and algorithms* are less considered. Moreover, the operational and strategic themes such as *mass customization, tracking, automation, mobile cranes*, and the like are noticeably neglected. The diverse nature of TA-MiC research is evident. It also reveals the current shortfall in studies in relevant aspects of modular construction, which are critical in facilitating the full integration and implementation of modular construction in the built environment. There is also disparity and lack of collaboration among MiC researchers and institutions, limiting the cross-fertilization of ideas and technology, resulting in MiC projects' digital divide across regions.

Nevertheless, the close industry-academia collaboration between the University of Alberta and PCL Industrial Management Inc in Canada is worthy of note.

Further in-depth analysis of the three critical phases of typical MiC projects shows that the prefab transportation phase, the logistics aspect concerned with the transportation of the precast modules from the prefab factory warehouse to the project site, is largely lagging in the application of DTT for its unique processes. Most of the research corpus articles focus primarily on applying DTT at either the OPM or OA phase. A follow-up quantitative analysis of the DTT employed in the TA-MiC research corpus shows that for the 15 main DTT used in the indexed dataset, the OPM phase of MiC experienced a greater utilization and application of DTT in its processes except for the "*Automated tools/systems*" DTT where the OA phase has a slightly more frequency of application. As earlier highlighted, the PB phase was the least digitalized phase of the MiC operational phases.

Generally, from the synthesis of the research corpus, there is a substantial gap in the lack of integration of this diverse DTT used in MiC projects. As a result, the study explores the potentiality of using BCT as a collaborative platform to integrate these DTT and support the overall coordination and management of data in MiC projects. Although blockchain adoption in the construction industry is still relatively low, the study envisioned that the industry has a lot to gain in the form of latecomer advantages. The several benefits of integrating some key DTT with blockchain were highlighted. We envisaged that the embrace of BCT would further lead to the digitalization and automation of the construction industry, inclusive of MiC projects.

Limitations of study. (i) The study's limitation lies in the data source's coverage (WoS) used for the scientometric and systematic analysis and the omission of non-English articles and conference proceedings. Also, the study focuses on research databases and do not consider other databases like patent databases like wipo.int or epo.org. (ii) The study’s findings and resultant statistics might change as more studies are published, and more DTT are adopted. Hence, more future review studies will need to be conducted to capture the new developments.

For future studies, development, or application of DTT in MiC projects, the following key research directions are proposed; (i) The limitations of some of the DTT employed in the previous studies identified in this research should be addressed towards developing a more holistic tool for the industry. (ii) Need for the development and deployment of DTT that addresses safety, automated supervision at prefabrication factories, robotics in prefab production and assembly, post-completion management of modular buildings, risk assessment and analysis, sustainability assessments, and the like. (iii) Practical synergy and application of several DTT across the MiC phases using blockchain or any automated system.

(iv) Explore how ethical standards or other regulatory policies could affect the deployment of DTT in MiC projects. (v) Cost-benefit analysis of the application DTT in MiC projects. (vi) How the application of DTT in MiC projects enhances green or smart buildings in the built environment.

Conclusively, the study has provided valuable insights and valuable guides to practitioners, researchers, government agencies, and even investors interested in venturing into MiC projects. The research network maps offer readers ready information to pinpoint future research collaborators, key areas to enhance MiC projects' implementation, and the various DTT and how they could be applied in future MiC projects. It also revealed the need for a holistic implementation of a collaborative system such as blockchain, which can serve as a fusion or centralized hub for integrating the DTT used across the MiC phases; and managing project data. The outlined benefits of employing blockchain can serve as a rallying point towards enhancing the construction industry's digitalization via its numerous capabilities, especially in reducing interoperability issues among DTT. The emerging knowledge areas identified in the study provide an avenue towards improving the efficiency and productivity associated with modular construction.

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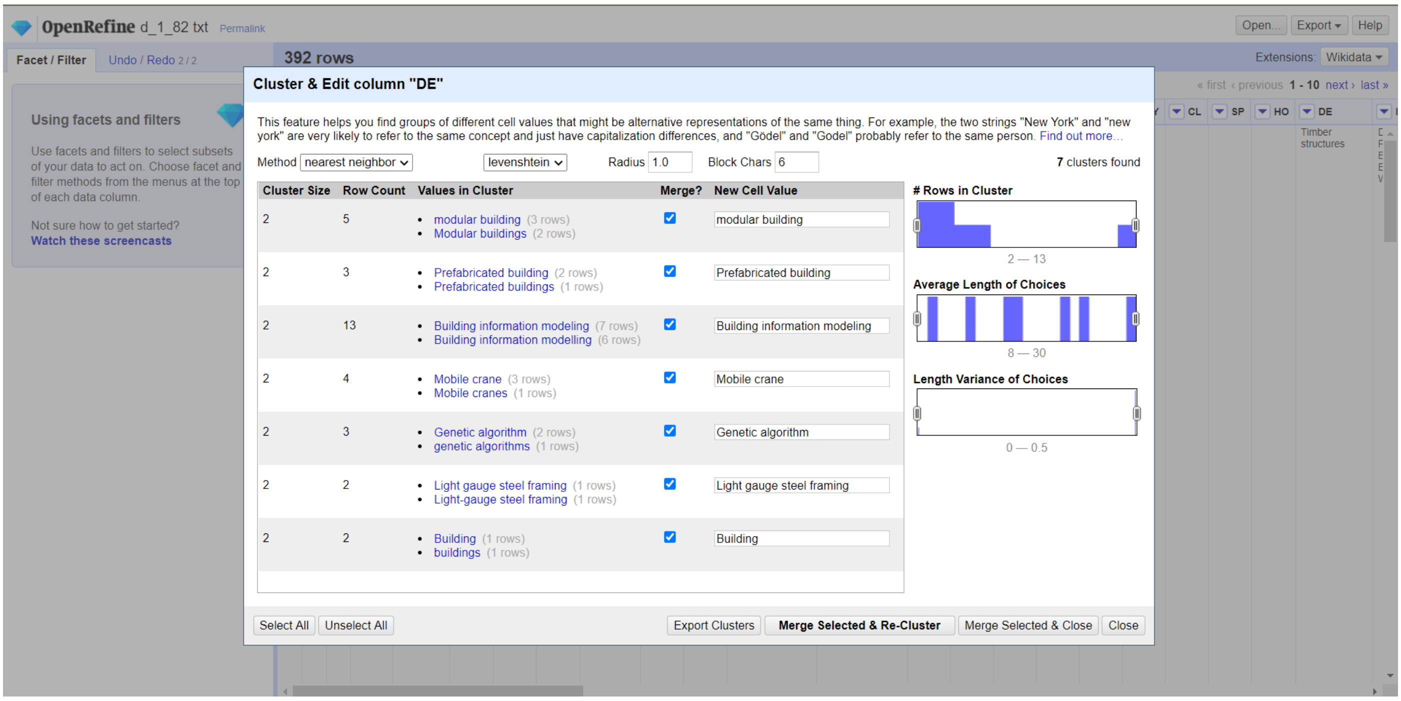
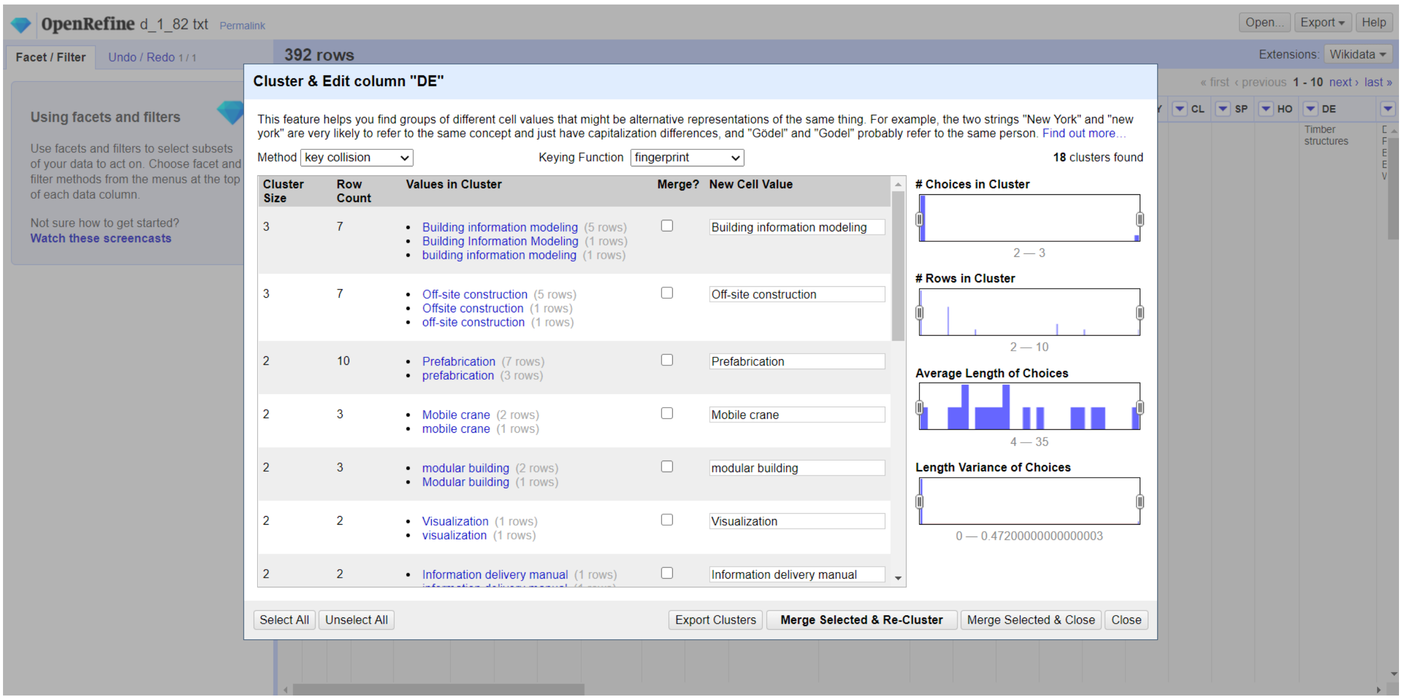
Appendix A: Data Refining and Clean up





Appendix B: Scientometric analysis of the research corpus on VoSviewer

Scientometric technique	Manuscript section (Table or Figure No.)	Approach to the quantitative analysis
1. Co-authorship analysis		
A. Prolific authors	Section 3.2.1.1 ‣ Table 2 ‣ Figure 4	The indexed and refined research corpus data were imported into the VoS viewer, and the type of analysis was set to "co-authorship" while the unit of analysis was set to "authors"; and the counting method as "fractional counting." A total of 253 authors were identified, and by setting the minimum number of documents and citations of an author to 3; 10 authors met the criteria threshold. This resulted in 5 authors' clusters.
B. Pre-eminent institutions	Section 3.2.1.2 ‣ Table 3 ‣ Figure 5	After importing the dataset into the VoS viewer, the type of analysis was similarly set to "co-authorship" while the unit of analysis was set to "organization"; and the counting method as "fractional counting." A total of 109 organizations were identified, and by setting the minimum number of documents and citations of an organization to 2; 20 organizations met the criteria threshold. This resulted in 11 organizations' clusters.
C. Leading countries	Section 3.2.1.3 ‣ Table 3 ‣ Figure 6	⌖ Type of analysis: "co-authorship"; Unit of analysis: "countries." ⌖ Counting method: "fractional counting." ⌖ Twenty-three countries were identified from the dataset. By setting the criteria threshold to 2 for the minimum number of documents and citations of a country, we have ten countries meeting the threshold. ⌖ Six countries clusters.
2. Co-occurrence analysis		
Knowledge areas	Section 3.2.2 ‣ Table 4 ‣ Figure 7	⌖ Type of analysis: "co-occurrence"; Unit of analysis: "all keywords." ⌖ Counting method: "fractional counting." ⌖ 450 keywords were identified in the dataset, and by retaining the default minimum number of occurrences of a keyword (5), 22 keywords met this criteria threshold. ⌖ Three keyword clusters were identified.
3. Citation analysis		
A. MCR publications	Section 3.2.3 ‣ Table 5	⌖ Type of analysis: "citation"; Unit of analysis: "documents". ⌖ 82 documents were identified from the dataset, and by setting the criteria threshold to 20 for the minimum number of citations of a document, 12 documents met the threshold. ⌖ Nine clusters were identified.
B. MCR publication sources	Section 3.2.4 ‣ Table 6 ‣ Figure 8	⌖ Type of analysis: "citation"; Unit of analysis: "sources." ⌖ 26 sources were identified from the dataset; and by setting the criteria threshold to 2 for the minimum number of documents and citations of a source, 10 sources met the threshold. ⌖ 5 clusters were identified.