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AUTHORS

Philip, AM; Prasannavenkatesan, S; Nustafee, N

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SIMULATION MODELLING OF HOSPITAL OUTPATIENT DEPARTMENT: A BIBLIOMETRIC ANALYSIS AND A LITERATURE CLASSIFICATION

ABY M PHILIP, Department of Production Engineering, National Institute of Technology, Tiruchirappalli, 620015, Tamil Nadu, India

SHANMUGAM PRASANNAVENKATESAN, Department of Production Engineering, National Institute of Technology, Tiruchirappalli, 620015, Tamil Nadu, India

NAVONIL MUSTAFEE, Centre for Simulation, Analytics and Modelling (CSAM), Exeter University, Exeter, EX4 4PU, UK

Author's addresses: A. M. Philip (corresponding author) Department of Production Engineering, National Institute of Technology, Tiruchirappalli, 620015, Tamil Nadu, India; email: abyphilips92@gmail.com; S. Prasannavenkatesan, Department of Production Engineering, National Institute of Technology, Tiruchirappalli, 620015, Tamil Nadu, India; email prasanna@nitt.edu; N. Mustafee, Centre for Simulation, Analytics and Modelling (CSAM), Exeter University, Exeter, EX4 4PU, UK; email: n.mustafee@exeter.ac.uk

Author's Bio: Mr. Aby M Philip is a Ph.D. scholar in the Department of Production Engineering, National Institute of Technology, Tiruchirappalli. His area of research is healthcare simulation. Dr. Prasannavenkatesan is an Associate Professor in the Department of Production Engineering, National Institute of Technology, Tiruchirappalli. His areas of interest include Healthcare simulation, E-waste management, and Supply chain Management. Dr. Navonil Mustafee is a Professor of Analytics and Operations Management, Director of Research (SITE), and Deputy Director for the Centre for Simulation, Analytics and Modelling (CSAM) at the University of Exeter. His research focuses on Modelling & Simulation (M&S) methodologies and their application in areas such as healthcare, supply chain management, and the circular economy.

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ABSTRACT

The increase in demand for outpatient departments (OPD) has contributed to overcrowded clinics and patient dissatisfaction. Computer simulation can help decision-makers meet the operational challenge of balancing the demand for outpatient services with considerations of available capacity. The paper presents a synthesis of the literature on simulation modelling in OPD using two approaches: a bibliometric analysis (employing keyword co-occurrence network) and a literature classification focusing on OPD strategy, OPD performance measures and simulation techniques. Our review is based on 161 papers, published between 2006 and 2020, identified through a methodological search of the literature. The objective of the review is threefold: (i) to identify the major and emerging research issues in general and specialized OPD, (ii) to find the commonly used performance measures in OPD and how it is associated with the strategies used to improve the performance, and (iii) to identify the commonly used simulation methods for OPD modelling. A key finding from the bibliometric analysis is that most OPD research can be classified under one of the four clusters – “organization and management”, “patient satisfaction”, “overbooking” and “performance”. We also find that patient waiting time has received much attention among the performance measures reported in the literature, followed by server idle time/overtime (server here is the OPD consultant or other healthcare resource). Our review serves as a key reference point for scholars, practitioners, students, and healthcare stakeholders, and those who use quantitative tools to aid operational decision-making.

Keywords: Outpatient clinic, Healthcare, Simulation, bibliometric analysis, co-occurrence, review

1 INTRODUCTION

An outpatient department (OPD) is the part of a hospital designed to treat patients that do not require admission as inpatients (Hong et al.[1]). OPD patients are generally referred to as outpatients. Inpatients discharged from hospitals also receive follow-up treatment in OPD. In many healthcare systems, the demand for OPD care is increasing. Clinical innovation, patient preferences and financial incentives are among the key drivers of the shift from inpatient facilities to outpatient delivery systems (Abrams et al.[2]). The prevailing COVID-19 pandemic has also shifted a significant amount of patient care to outpatient settings (Jessica et al.[3]). Considering the increasing demand for OPD care, many healthcare systems are set to either invest in new facilities or expand their existing outpatient services Abrams et al.[2].

As OPD demand increases, meeting the demand for high-quality care within the limitations of resources and capacity remains an operational challenge. To improve healthcare delivery in OPD, researchers have focused on strategies such as appointment systems in outpatient services (Cayirli and Veral.[4]; Ahmadi-Javid et al.[5]), patient flow and routing (Jun et al.[6]), and resource allocation (Mielczarek and Uzialko-Mydlikowska[7]). Computer modelling and simulation (M&S) approaches have also been widely used (Hong et al[1]). M&S allows for the experimentation of strategies to improve metrics associated with productivity and efficiency (Crema and Verbano[8]), patient throughput and waiting time (Naiker et al.[9]) (Shoaib and Ramamohan[10]), and service quality (Hong et al.[1]; Roy et al.[11]). An increasing number of M&S studies now use a combination of simulation techniques such as discrete-event simulation, system dynamics and agent-based simulation in the context of a single simulation study; this is referred to as hybrid simulation (Mustafee et al.[12]). Brailsford et al.[13] reported that healthcare is one of the main areas of application for hybrid simulation due to the need to model a higher level of complexity of the underlying system. The application of simulation has been instrumental in addressing the multifaceted challenges faced in the healthcare domain (Zeltyn et al.[14]).

The increasing popularity of healthcare simulation has led to an increase in the volume of literature, and with it, the number of review articles in this area of research (e.g., Jun et al.[6]; Fone et al.[15]; Katsaliaki and Mustafee[16]; Roy et al.[11]). OPD forms a distinct sub-set of this overarching literature. OPD literature can be classified further into articles focussing on specialist outpatient departments (SOPD) and general outpatient department (GOPD). In our review, GOPD refers to a non-specialized healthcare provider offering primary and general treatment for patients with all types of medical conditions. GOPD providers offer diagnostic services, patient screening for referrals and treatment for ailments which do not need any specialist consultation. The specialist outpatient clinics or SOPD include those dedicated to speciality services such as orthopaedics, surgery, paediatrics, ophthalmic, obstetrics and gynaecology. The research on SOPD is fairly developed due to the rapid growth of specialized hospitals with better amenities and the reliance on patient-centred care.

The paper presents a synthesis of the literature on simulation modelling in OPD using two complementary approaches, namely, bibliometric analysis and a literature classification. We employ a methodological search of the literature, also referred to as structured literature review (SLR), using two abstract databases (*Scopus* and *Web of Science*) to identify the initial set of 1955 articles. Following this, through abstract screening, we identify a sub-set of 161 articles. The 161 articles serve as the dataset for both the bibliometric analysis and the literature classification. **(a) Bibliometric analysis**: Several studies have employed meta-data and bibliometric techniques for the analysis of M&S literature (e.g., Mustafee et al[17]; Gore et al[87]; Diallo et al[19]). There are various forms of this analysis, for example, analysis of co-citation networks, keyword co-occurrence networks, and cluster analysis. In this paper, we employ a *keyword co-occurrence network*. (b) **Literature classification**: This involved the full-text reading of the 161 papers to present a comprehensive profile (classification) of the OPD literature focusing on OPD strategy, OPD performance measures and simulation techniques that are most commonly reported in OPD studies. We classify the literature under SOPD and GOPD (we use the overarching term OPD when the context of usage applies to both SOPD and GOPD). Furthermore, the SOPD literature is further classified into 18 specializations. In summary, this paper's findings are based on bibliometric analysis (using metadata from the published articles) and literature classification (employing full-text reading), with the SLR providing the underlying dataset of papers for the two distinct forms of analysis.

The paper is organised as follows. In section 2, we present an overview of existing review papers on OPD and outline the contribution of our review. Section 3 presents the review method. Section 4 presents the findings from the bibliometric analysis. The analysis is presented under the three sub-sections, namely, descriptive analysis (Section 4.1), the thematic strategic diagrams and findings from the cluster analysis (Section 4.2). A comprehensive classification of the literature is presented in Section 5. The analysis in this section focuses on OPD strategy (Section 5.1), OPD performance measures (Section 5.2) and simulation techniques (Section 5.3). Section 6 summarizes the key research findings and the limitations of this study.

2 EXISTING LITERATURE REVIEWS ON OPD

Table 1 summarises the existing reviews of simulation in healthcare with a focus on OPD. It is observed that the reviews are either on multiple healthcare services (including OPDs) or specific to only OPDs. As listed in Table 1, the earliest review paper in this domain was published by Jun et al.[6] and focussed on patient scheduling and admissions**,** facilities (operation room) planning and staffing strategies for outpatient clinics to improve patient throughput and waiting times**.** Gunal and Pidd[20], Mielczarek and Uziako-Mydlikowska[7], Katsaliaki and Mustafee[16], Hulshof et al.[21], Crema and Verbano[8], Roy et al.[11] reviewed the potential of simulation in solving multiple healthcare services, including OPD. Cayirli and Veral[4], Fone et al.[15] and Gupta and Denton[22], Ahmadi-Javid et al.[5] reviewed the appointment system and admission policies for regulating the patient flow in outpatient clinics. Hong et al.[1] analysed the appointment scheduling, resource allocation, and patient flow together in an OPD. Naiker et al.[9] identified resource realignment, operational efficiencies, and process improvement as strategies to reduce outpatient waiting times.

For studies reported in the table 1, we included the author and year, review period, type of review, namely, narrative literature review (NLR) and structured literature review (SLR), OPD strategies, performance measure, and simulation approaches presented. The simulation approaches are identified as MCS (Monte-Carlo simulation), DES (discrete-event), SD (system dynamics), ABS (agent-based) and HS (hybrid simulation). Many studies are narrative and focus mainly on appointment scheduling and admission. Only a few researchers (Naiker et al[9]; Crema and Verbano[8]) have reviewed the association between the strategies and performance improvement in OPD services. The performance measures reported in the existing reviews are classified as economic (such as resource cost, the cost associated with waiting time, cost of idle time/overtime, cost related to no-show, inconvenience cost) and service-based (this includes patient waiting time, length of stay, server idle time, over time, throughput, and service quality). It is observed that the existing reviews mainly investigated the use of the three simulation modelling techniques (MCS, DES, and SD).

As the volume of literature on OPD continues to grow (Naiker et al[9]; Ahmadi-Javid et al[5]), there are opportunities to complement existing studies and present a synthesis of the *overall* and *updated* body of work. There are also opportunities for incorporating broader methodological approaches for literature reviews, such as bibliometric analysis, as is the case in this paper. A structured review (SLR) has certain advantages over narrative-based reviews - it is replicable, scientific, fact-based, and transparent (Tranfield et al[23]). An SLR avoids potential bias due to the well-developed methodological standards for the database search, article selection, and synthesis of the research results (Roy et al[24]). In this work, we have adopted the approach presented in Anandh et al[25], where an SLR identifies the papers for the review, bibliometric and network analysis tools are then used to perform data analysis, data synthesis, and for interpretation. The bibliometric analysis enabled the identification of the current and emerging research themes in OPD and its evolution over two distinct sub-periods (2006-2013 and 2014-2020). Our review differs from existing reviews in the following aspects:

- Our review is specific to OPD simulation. It aims to identify the multitude of OPD-related themes that have been extensively researched in the past, the current research, and emergent new research areas.
- Our review employs bibliometric methods and a more traditional literature classification approach. Using the two techniques, we present a comprehensive snapshot of the application of M&S in OPD.
- Our review summarizes the commonly used simulation approaches to model OPD and provides direction for future research.
- We present a comparison of the findings of our review paper with the existing reviews and report on how our work aligns with the earlier findings.

3 REVIEW METHOD

A systematic literature review (SLR) approach is adopted following Denyer and Tranfield[26]. The approach consists of four phases (see Figure 1). In the following sub-sections, three of the SLR phases are described, namely, formulation of research questions (section 3.1), literature search strategy and identification of relevant articles for subsequent analysis (3.2), and the bibliometric methods for data analysis (3.3). Discussions pertaining to phase 3 of the SLR (Figure 1) are split into two sections, with 3.3.1 and 3.3.2 focusing on keyword co-occurrence network and thematic strategic diagram, respectively. The findings derived using these methods are the subject of section 4 on results and analysis.

3.1 Research planning and formulating the questions

Our literature review is motivated by the following three research questions (RQs):

- **RQ1:** What are the significant and emerging research issues in general and specialized OPD?
- **RQ2:** What are the commonly used performance measures in OPD, and how are they associated with the strategies used to improve performance?
- **RQ3:** What are the commonly used simulation approaches (DES, SD, Agent, Hybrid, and MCS) to model OPD?

- Our study uses keyword co-occurrence network (KCON) analysis as it is a widely used bibliometric method that maps the pertinent literature directly from the interactions of the keywords (Rajagopal et al[27]). KCON analysis assumes that a group of keywords could indicate the underlying themes and that the co-occurrences of keywords could reveal the association with the underlying themes (Hu & Zhang[28]). The higher the co-occurrence frequency of two keywords, the greater the correlation (Liu et al[29]). KCON analysis is used to visualize and frame this domain's mature and emerging themes **[RQ1]**. The study of the links between the thematic clusters highlights the association between the themes. The shortlisted articles are comprehensively analysed to answer the research questions **[RQ2]** and **[RQ3]**.

3.2 Literature search and article selection

The literature search involves the choice of database, keywords, article search, screening and applying the inclusion/exclusion criteria. It is recommended that a minimum of two databases be searched to avoid selection bias (Key[30], Bramer et al[31]). The *Web of Science (WoS)* and the *Scopus* databases are used in this research. They are the largest multidisciplinary databases of quality academic journals and provide bibliographic information on research articles (Mongeon and Paul-Hus[32]). Echchakoui[33] reported that merging the results from both WoS and the Scopus databases improves the reliability of the bibliometric analysis.

A three-level keyword formulation is defined, as shown in Table 2. Level 1 explicitly used the terms specific to OPD and healthcare as the focus of this review is limited to OPD. We used ambulatory as a keyword as ambulatory care services have similar characteristics to the outpatient clinic, as both facilitate same-day discharge and provide care to patients without offering a room or bed (Hulshof et al[21]). A set of level 2 keywords specific to strategies and performance is used for collecting the relevant articles. The level 3 keywords are specific to simulation modelling approaches. The keywords within each level are connected by ‘OR’ and between each level by ‘AND’. The exact search string is used for both WoS and Scopus databases. We limit our article search in both databases from 2006 to May 2020. The works before 2006 were excluded since we retrieved only a limited number of articles on OPD services that used simulation, for example, Cayirli and Veral[4], Fone et al[15] and Jun et al[6]. Our search retrieved 1955 articles (WoS:1164; Scopus: 791) up to May 2020. Of the 1955 articles, 1675 unique articles are retained after removing the duplicates.

Table 1: Existing literature reviews on simulation in healthcare with a focus on OPD

Sl No	**Author & Year**	**Review period**	**NLR**	**SLR**	**Strategies for OPD services**			**Performance measures**		**Simulation Approach**					
					Appointment System/scheduling/ no-show/lateness	Patient flow & routing	Resource allocation/ capacity planning	Economic	Service	Simulation optimisation	MCS	DES	SD	ABS	HS
1.	Jun et al[6]	1970-1999	•		•	•	•		•			•			
2.	Cayirli and Veral[4]	1952-2002	•		•	•		•	•		•	•			
3.	Fone et al[15]	1980-1999		•	•			•	•		•	•			
4.	Gupta and Denton[22]	Before 2008	•		•		•	•	•	•					
5.	Gunal and Pidd20	2000-2008	•		•		•		•			•			
6.	Mielczarek and Uzialko-Mydlikowska[7]	1999-2006	•		•		•	•	•		•	•	•		
7.	Katsaliaki and Mustafee[16]	1970-2007		•	•	•	•	•	•		•	•	•	•	
8.	Hulshof et al[21]	1952-2012		•	•		•		•	•					
9.	Hong et al[1]	1962-2012	•		•	•	•		•	•	•	•	•		
10.	Ahmadi-Javid et al[5]	2003-2016	•		•	•	•		•	•					
11.	Naiker et al[9]	Before 2015		•	•		•		•	•					
12.	Crema and Verbano[8]	2005-2016		•		•			•			•	•	•	
13.	Brailsford et al[13]	2000-2016		•		•	•		•						•
14.	Roy et al[11]	2007-2016	•		•	•	•	•	•		•	•	•	•	

Note: MCS: - Monte Carlo Simulation, DES: - Discrete Event Simulation, SD: - System Dynamics, ABS: - Agent Based Simulation, HS: - Hybrid Simulation

Table 2: 3- Level keyword used in WoS and Scopus search

Level 1: Outpatient* OR "walk-in patients",
AND
healthcare* OR hospital OR paediatric* OR ambulatory* OR gynaecology OR orthopaedics OR neurosurgery OR physiotherapy OR chemotherapy OR perinatology OR ophthalmology OR oncology OR obstetrics OR surgery OR dental OR dermatology OR endocrinology OR cardiology
AND
Level 2: schedule* OR appointment* OR "capacity planning" OR capacity OR "resource planning" OR "resource allocation" OR "patient flow" OR "patient routing" OR congestion OR "waiting time" OR "patient satisfaction" OR "length of stay" OR queue* OR emergency OR no-show OR overbooking OR unpunctuality OR overtime OR consultation OR throughput OR service time OR "transit time" OR "quality of service" OR "service efficiency" OR "patient mix" OR "outpatient services" OR "service operations" OR "patient quality of care" OR "turnaround times"
AND
Level 3: Simulation OR "Monte Carlo*" OR "system modelling" OR "system dynamics" OR "discrete event simulation" OR "agent simulation" OR "agent modelling" OR Markov* OR "simulation-based decision support system" OR hybrid OR simulation optimisation

[Insert Figure 1: Proposed review method. Adapted from Denyer and Tranfield[26]]

Screening and inclusion: We included journal articles written in English and excluded conference proceedings and book series. Articles on OPD reporting optimization, descriptive statistics related to OPD outcome measures, heuristics, and papers that were not on computer simulation were excluded. Similarly, simulation studies that were not relevant to outpatient clinics/issues were also excluded. The initial screening/scanning is done manually in relation to the stated inclusion/exclusion criteria (the inclusion and exclusion criteria are mentioned in Figure 1). The appraisal was conducted systematically, using an MS-Excel spreadsheet which contained the meta-data for the papers, e.g., article title, abstract, keywords, authors, journal, and the year of publication. To minimize the bias in article screening, two authors (1 and 2) independently reviewed the 1675 articles based on the title, abstract, and keywords and shortlisted 176 articles. These articles were read by the third author (abstract and the meta-data for the papers; this took approx. 14 hours of total reading time – approx. five minutes for each abstract). 15 articles were subsequently removed as these papers primarily focussed on mathematical modelling rather than a computer simulation. Our screening strategy thus resulted in a total of 161 papers for full-text review. The composition of the final set is illustrated in Figure 2. The number of publications retrieved from Scopus was 42% more than those from WoS. It is also observed that 50% of the records were common to both WoS and Scopus.

[Insert Figure 2: The composition of the final dataset (WoS:12; Scopus: 68; Common to both: 81)]

3.3 Bibliometric Analysis

Bibliometric analysis is used to identify, organize, and analyse the significant evolution and trends within a specific research field (Aznar-Sanchez et al[34]). Bibliometric analysis can be categorized into three groups: Review techniques, evaluative techniques, and relational techniques (Fabregat-Aibar et al[35]). Among these, the relational techniques explore the structural and dynamic aspects of a research field using article citation, co-citation, bibliometric coupling, co-author, and co-occurrence/co-word as the unit of analysis (Zupic and Cater[36]). Co-occurrence analysis is the only bibliometric method that maps the pertinent literature directly from the interactions of the keywords (Zhao & Zhang[37]). Studies have used co-occurrence analysis to determine the knowledge structure in various research fields (Jose and Shanmugam[38]). Science mapping tools like *Bibexcel, CiteSpace, CitNetExplorer, SciMat, Sci2Tool* and *VOS viewer* are available to conduct the bibliometric analysis (Moral-Munoz et al[39]). Among these, *SciMat* is suitable for the quantitative content analysis and dynamic analysis of the themes (Thome et al[40]). Various visualization tools are available in SciMat, such as strategic diagram, cluster network, evolution map, and overlapping map which are used to identify the research themes. We used SciMat, an open-source bibliometric tool, because of its versatility and easy interaction with other software (Moral-Munoz et al[39]; Cobo et al[41]). The input for SciMat should be in either the research information system (*.ris-Scopus) or in text format (*.txt-WoS). We used *Microsoft Word* to organise and maintain the formats of the retrieved metadata into a single format (*.txt). Usually, the metadata from the bibliographic database contains errors, so a pre-processing of meta-data to remove the duplicates and misspelt items are needed.

3.3.1 Keyword co-occurrence analysis:

Keywords effectively describe the contents of a paper. Two keywords have a semantic relationship if they occur together in an article. The higher co-occurrence frequency of two keywords implies a more significant correlation between the keywords (Jose and Shanmugam[38]). There are two keyword types for articles (i) *author keywords* (in both WOS and Scopus), and (ii) *keyword plus* (in WoS) or *index words* (in Scopus). *Author keywords*, as the name suggests, are identified by the authors of the paper.

On the other hand, the *keyword plus/index words* are derived from an algorithm developed by Clarivate Analytics (WoS) or from thesauri that Elsevier owns (Scopus). Out of 161 articles, 55 articles have *author keyword*, *keyword plus*, and *index keyword*; 19 articles include *author keyword* and *keyword plus*; 50 articles have *author keyword* and *index keyword*. In the literature, three keyword categories have been used in the co-occurrence analysis to enhance the search power and result in more high-frequency words to map the knowledge structure of the research domain (Roy et al[24]). For the first sub-period (2006-2013), 122 *author keywords*, 54 *keyword plus*, and 420 *index keywords* were retrieved with an occurrence frequency of 1163. Similarly, for the second sub-period (2014-2020), 227 *author keywords*, 148 *keyword plus* and 700 *index keywords* were obtained with an occurrence frequency of 2436. Following the work of Roy et al[24], *author keywords* and *keywords plus/index words* were merged into one file after removing the similar keywords for both sub-periods.

Keywords often need to be standardized as authors use different words to describe the same meaning. First, plural keywords were converted to their singular form (such as appointment systems, appointment system), hyphenated words (Health-care, Healthcare), and spelling variants (Optimisation, Optimization) were standardized. Next, similar keywords such as ‘Physiotherapy’ .and ‘Physical therapy’ were standardized. Further, the keywords with a single frequency which did not have a similar term in our list were excluded as they could not be mapped. Following Khasseh et al[42] and Roy et al[24], we defined a threshold value of two or more occurrences of keywords for the two sub-periods of analysis. For sub-period 1 (2006-2013), this resulted in a total of 35 *author keywords* and 10 *keywords plus*, with a total frequency of 203 (61.32% of the 331 occurrences). For sub-period 2 (2014-2020), the threshold of >= 2 resulted in 63 *author keywords* and 41 *keyword plus*, with a total frequency of 522 (66.07% of the 790 occurrences). As the number of *index keywords* (Scopus) were more than double compared to *author keywords* and *keyword plus* (WoS), a growth analysis was carried out (Uddin, Khan, & Baur[43]) to identify the high-frequency index keywords for inclusion. Each sub-period is divided into three-time segments, and index keywords that occurred in less than two contiguous time segments were excluded considering the growth criterion. Finally, we selected 16 and 20 *index keywords* for sub-periods 1 and 2, respectively, based on the computed growth score.

The keyword co-occurrence network (KCON) represents each keyword as a node, and a link between two keywords is formed between keywords listed in the same paper. The edge weight between two keywords represents the number of common documents listing both the keywords. The cluster analysis and strategic diagram help to visualize the relation between the keywords. A simple centre algorithm is widely used in clustering as it is not complex and well known (López-Herrera et al[44]). SciMat provides this clustering algorithm, which helps build the map (Cobo et al[41]).

3.3.2 Thematic strategic diagram:

The strategic diagram plots the clusters according to their density and centrality. The density represents the internal strength (local context) of a cluster which also indicates a measure of maturity and sustainability of a research theme, whereas centrality (global context) measures the correlation of one cluster with the rest (Callon et al[45]). Clusters with high centrality occupy a central and vital position in the entire research field. Typically, the theme clusters are in four quadrants to indicate the maturity of the research themes, considering the different centrality and density. In *quadrant I* (refer to Figure.5), with high centrality and density, the research themes are mature and central in the overall research field and are identified as the motor theme. In *quadrant II*, the research themes are central but undeveloped and denote the transversal or basic theme. In *quadrant III*, the research themes are peripheral and developed and form an isolated theme. In *quadrant IV*, with low density and centrality, the research themes are peripheral and undeveloped or immature and considered either emerging or disappearing (Callon et al[45]).

4 RESULTS AND ANALYSIS

Section 4.1 presents a descriptive analysis of the dataset used for the bibliometric analysis. It includes a year-wise analysis of papers published (A), geographical analysis of contribution based on author affiliation (B), top 10 publication outlets (C), and keywords' evolution in two distinct periods (D). The source of the descriptive analysis is the 161 articles identified through the structured review, followed by a manual compilation of the information related to publication year, authors, journals and author keywords. Following this, section 4.2 presents the bibliometric analysis (refer to section 3.3, which describes bibliometric method in detail). Finally, section 4.2.2 and 4.2.4 presents cluster analysis based on KCON for sub-periods 2006-2013 and 2014-2020, respectively.

4.1 Descriptive Analysis of the Data Set

(A) **Year-wise analysis**: The year-wise distribution of 161 articles in our final dataset is shown in Figure 3. Our analysis shows that, since 2006, the volume of literature published in this area has maintained a consistent trajectory of growth (the exception being 2008); the volume of literature has especially grown since 2011.

[Insert Figure 3: Distribution of reviewed articles by year]

(B) **Author analysis**: Table 3 presents an analysis of the authors' contribution in terms of the geographic location of their primary affiliation. Most studies were from the USA (36.6 %), followed by Canada (11.1%) and the Netherlands (8.69%). Few recent studies (Naiker et al[9]; Roy et al[24]) have also reported that the highest number of publications belongs to the authors that are affiliated to institutions in the USA. Authors affiliated to Indian, Chinese, Australian, and Taiwanese institutions contributed to four papers each.

Table 3: Author contribution based on the geographic location of their primary affiliation

Country	Authorship count	Country	Authorship count
USA	59	**UK**	7
Canada	18	**Australia**	4
The Netherlands	14	**China**	4
Japan	8	**India**	4
Turkey	8	**Taiwan**	4

(C) **Journal analysis**: Table 4 lists the top 10 journals which have published papers related to the use of simulation in the context of OPDs. The journal *Health Care Management Science* (HCMS) is the outlet that has published most papers in this area (14). This is not surprising since HCMS focuses on using quantitative methods for informing decision-making related to the delivery of health care. Two *UK Operational Research Society* (ORS) journals feature in the list (*Journal of the Operational Research Society* and the *Journal of Simulation*) with a combined total of 13 papers. However, the number of authors with UK affiliations is only seven (Table 3). Of the top ten journals, only *Production and Operations Management* and the two ORS journals are not specific to healthcare or medicine. This demonstrates that this research has also found a conduit in more mainstream journals (i.e., not specific to a domain), competing effectively with papers from wider application areas and using other OR/MS methods.

Table 4: List of top the ten journals that have published research in the area of simulation and OPD

Sl No.	Journal	No
1	HealthCare Management Science	14
2	Journal of the Operational Research Society	10
3	International Journal of Health Care Quality Assurance	6
4	Health Systems	6
5	IISE Transactions on Healthcare Systems Engineering	6
6	Production and Operations Management	5
7	Journal of Healthcare Engineering	5
8	BMC Health Services Research	4
9	Artificial Intelligence in Medicine	3
10	Journal of Simulation	3

(D) **Keyword analysis:** For the analysis of keywords selected by the authors (subsequently referred to as author keywords), we used an analysis approach similar to the one presented in Mustafee and Katasaliaki[46] where keywords were analysed under two sub-periods. The top 10 *author keywords* and their corresponding frequencies for the sub-periods of 2006-2013 and 2014-2020 are shown in Figure 4. *"Simulation"* is the most frequently used keyword for both sub-periods. Following this, the keywords with relatively high frequencies in both the sub-periods are *"Healthcare"*, *"Discrete Event Simulation"* (combined with *"Queuing Theory"* with four instances from period one), and *"Outpatient Clinics"* (combined with the keyword *"Outpatient"* with eight instances in). Our findings related to the importance of the four keywords (*"Simulation", "Discrete Event Simulation/Queuing Theory"*, *"Healthcare"*, *"Outpatient Clinics/Outpatients"*) is not surprising when we consider the search terms that used to identify the underlying set of papers (Table 2). However, our analysis of author keywords has identified the shift in the relative importance of some of the topics. For example, the literature on *"Appointment Scheduling"* has grown over five times during the two periods. Arguably, the ageing population in many developed countries have meant that OPD appointments have experienced a manifold increase. This may explain the astonishing growth of research in scheduling strategies to help attain KPIs related to OPD wait times (e.g., 14-week wait from GP/Physician referral to the patient being seen in OPD). Three new author keywords reported in the second period are *"Patient Flow"*, *"Markov Decision Process"* and *"Simulation Optimization". "Waiting Time"* remains an important author keyword for both periods.

[Insert Figure 4: Evolution of top ten author keywords during the sub-periods 2006-2013 and 2014-2020]

4.2 Bibliometric Analysis using Keyword Co-occurrence Network

This section presents the analysis of the clusters for two distinct sub-periods, namely, 2006-2013 (sub-period 1) and 2014-2020 (sub-period 2). As illustrated in Figure 1 (proposed review methodology), the retrieved metadata from both the database in Phase II is input into SciMat for KCON Phase III analysis (frequency reduction set to value two and maximum and minimum network size set to value six and three for 2006- 2013 and nine and three for 2014 – 2020). The analysis results in six clusters for period one (2006-2013) and nine clusters for period two (2014-2020).

4.2.1 Thematic strategic diagram for sub-period 2006-2013:

In this sub-period, 61 keywords from 54 articles (35 author keywords; 10 keyword plus; 16 index keywords) were retrieved. Keyword co-occurrence analysis resulted in 6 clusters, as shown in the strategic thematic diagram in Figure 5. The clusters "Article", "Waiting lists", "Healthcare", and "Time" are identified as the motor theme depicting the ongoing research during this sub-period (refer section 3.3.2). "Management" and "Discrete event simulation" form the peripheral and undeveloped theme. Table 5 describes a summary of the research focus of each cluster during this period.

[Insert Figure 5: Strategic diagram for sub-period 2006-2013]

4.2.2 Cluster analysis for the sub-period 2006 to 2013:

Figures 6 illustrate the network of clusters for the first sub-period. The network visualisation was constructed using Pajek (Anandh et al[25]) and modified using INKscape (Doppler & Newton[47]). In the network diagram, the size of the cluster is proportional to the number of keywords associated with it. The nodes of each cluster represent keywords, and each node's colour represents the cluster to which it belongs. Each cluster is labelled by the keyword that forms the cluster's center. For example, in Figure 6, "DES" is labelled for a cluster that describes mainly hybrid optimization with DES. Since DES is a central word in that cluster by default, it is labelled as DES. The node's size in each cluster is proportional to the number of core documents (articles) it is linked to. The lines between the nodes are established based on the equivalence index (Cobo et al[41]). The coloured lines denote the link strength within the clusters, and the black lines depict the links among the clusters. The cluster with the maximum number of external links with more than one cluster is known as the "primary" cluster, and the other clusters are the "secondary" clusters. It is observed that all the clusters have an external link with more than one cluster, which makes all the clusters "primary" clusters. The cluster "Waiting lists" is the only cluster with external links with all other clusters, making it the central theme of the network. "Primary" clusters include "Waiting lists", "Article", "Healthcare", "Time", "DES", "Management", All the internal links of clusters are maintained, whereas external links with link weightage less than 0.14 are removed to better view the external network using Pajek. Table 6. shows the relationship between the clusters based on two measures: the number and weight of links between the clusters. The total number of links and maximum link weight between the clusters are obtained from SciMat. The average number of links between clusters is obtained by taking the ratio of the existing number of links between clusters and the total number of possible links between clusters (Anandh et al[25]).

[Insert Figure 6: Links between clusters for the period of 2006-2013]

Table 5: Research focus of clusters for sub-period 2006 to 2013 [Ref. supplementary data to identify the cited references in bracket]

Theme	**Cluster label**	**Sub-themes internal link weight**			**Subthemes**	**Description**
		Node A	Node B	Link weight		
Central and developed	Article	Article	Human	0.93	Simulation	Research in this cluster investigate the relationship between factors such as no shows [13, 1, 4, 38], walk-ins [34, 44, 1, 38, 30], appointment system [8, 13, 17, 34], capacity/workload/staffing levels [2, 22, 20, 40] on patient service performance that includes waiting time [9,17,45], access time [2], congestion/patient flow [10, 44, 5, 20] patient throughput [33, 4, 20], quality improvement [44] and physician's idle time/overtime [17, 13, 35, 44]. Simulation models specifically DES [2, 9, 22, 34, 28, 35, 43, 44, 3] are used to test different scenarios using empirical data.
		Article	Outpatient clinic	0.56	Outpatient clinic	
		Article	Simulation	0.54	Human	
		Simulation	Human	0.54	Appointment scheduling	
		Human	Outpatient clinic	0.54	Hospital management	
	Waiting list	Hospital admission	Waiting lists	0.39	Hospital	This cluster focuses on policy alternatives to solve the long waiting list in OPD such as patient registration [10], capacity/workload allocation [33], pooling of patient groups like regular/urgent, first time/follow-up [18], that reduces capacity variability [10] and maximum waiting times [2, 17, 34] for consultation without increasing the use of health care resources. Radiology outpatient department has received significant research attention [18, 32, 33].
		Waiting lists	Radiotherapy department	0.38	Hospital admission	
		Consultation	Hospital admission	0.25	Consultation	
		Consultation	Waiting lists	0.25	Radiotherapy department	
		Waiting lists	Variability	0.25	Variability	
	Healthcare	Systems	Patient flow	0.27	Appointment system	This cluster analyses the appointment system schemes for outpatient scheduling [26] to reduce access time [8] and waiting time [1, 13]; Real time scheduling [16], block scheduling [26] and integrated scheduling [27] with patient flow [16] received considerable attention.
		Systems	Appointment system	0.23	Scheduling	
		Appointment system	Service	0.23	Patient flow	
		Systems	Healthcare	0.19	Systems	
		Healthcare	Patient flow	0.18	Service	
	Time	Time	Ambulatory care Facilities	0.31	Outpatient	Research in this cluster investigates how to mitigate patient waiting time and improve patient satisfaction [36, 54] with a specific focus on ambulatory care settings [1]. Studies on outpatient clinics in USA [20, 48] received substantial attention.
		Ambulatory care facilities	USA	0.17	Ambulatory care facilities	
				0.17	Patient satisfaction Patient wait time	

		Ambulatory care facilities	Patient waiting time	0.16	USA	
		Outpatient	Time	0.15		
		Outpatient	Patient satisfaction			
Peripheral and undeveloped	Management	Health	Management	0.27	Health	Management of health care services related to outpatient is presented within this cluster [8,15,16]
		Care	Management	0.22	Care	
		Care	Health	0.13		
	Discrete event simulation	DES	Efficiency	0.15	Waiting time	Research in this cluster addresses the opportunities and challenges of using DES on OPD. Queuing theory is used with DES to improve throughput and reduce waiting time [32, 35]. Scheduling [46] and capacity planning [43, 49] are proposed to enhance the efficiency of healthcare
		DES	Capacity planning	0.15	Queuing theory	
		DES	Queuing theory	0.08	Capacity planning	
		Waiting time	DES	0.03	Efficiency	

Similarly, the average link weight is the ratio of the sum of all link weights (equivalence index) between the clusters and the total number of links. The more the number of links and the stronger the links, the more these clusters describe research problems considered necessary by the scientific community (Callon et al[45]). Cluster "Waiting lists" has more connection with cluster "Article", whereas the maximum link weight is found between cluster pairs "Article" and "Time", followed by "Waiting Lists" and "Article". Similarly, the average number of links is high among the cluster-pairs "Article" and "Time" and "Waiting lists" and "Article". The average link weight, which provides the strength of association between clusters, is found to be high among cluster pairs "Article" and "Time", followed by "Waiting lists" and "DES", and "Waiting lists" and "Management". Accordingly, the research during this sub-period focussed on using DES to evaluate the policy alternatives such as the appointment system and capacity/resource allocation to solve the long waiting list in OPD.

Table 6: Links between clusters for the sub-period 2006 to 2013

Cluster A	**Cluster B**	**No. of links**		**Link weight**	
		Total	Average	Maximum	Average
Waiting list	Time	3	0.08	0.23	0.18
	Article	18	0.50	0.38	0.21
	DES	3	0.10	0.33	0.23
	Management	1	0.06	0.23	0.23
	Healthcare	2	0.06	0.25	0.19
Article	Time	22	0.61	0.5	0.28
	DES	5	0.17	0.21	0.16
	Healthcare	2	0.06	0.24	0.20
Healthcare	Management	1	0.06	0.22	0.22
Time	DES	1	0.03	0.19	0.19

4.2.3 Thematic strategic diagram for sub-period 2014-2020:

In this period, 107 articles of 161 articles are present; there is an increase in the number of articles compared to the first sub-period. 124 keywords (63 author keywords, 41 keywords plus, and 20 index keywords) were retrieved. Keyword co-occurrence analysis resulted in 9 clusters, as shown in the strategic thematic diagram in Figure 7. Research focus can be identified using these clusters. From Figure 7, the clusters 'Organization and management", "patient satisfaction", "overbooking", "performance" form the central theme and represent the ongoing and frequently appearing research. Clusters "Model", "discrete event simulation", and "appointment system" form emerging themes. "Algorithm" creates the central and undeveloped theme, and "Orthopaedics" is regarded as a more specialized and relatively isolated theme from the core domain (refer section 3.3.2). The central theme identified in period 1, namely, "Waiting lists", "Healthcare" and "Time", is a subtheme to the central theme of period 2. Table 7 shows a summary of the research focus of each cluster during this period.

[Insert Figure 7: Strategic diagram for sub-period 2014-2020]

Table 7: Links between clusters for the sub-period 2014 to 2020 [Ref. supplementary data to identify the cited references in bracket]

Theme	Cluster label	Subthemes internal link weight			Sub-themes	Description
		Node A	Node B	Link weight		
Central and developed	Organisation and management	Female	Male	0.85	Simulation	This cluster focuses on policies such as capacity planning [78, 153], resource allocation [98,100], registration system [81] to manage patient throughput [107, 62], patient flow [73, 83, 87, 90, 125, 134, 153], patient access [65] to reduce waiting time [68, 83, 81, 84, 86, 98, 109, 117, 158, 100, 85, 89, 132, 152]. Ambulatory care clinics have received considerable attention [115,132]. Simulation approaches such as DES [65, 68, 78, 84, 91, 94, 96, 107]; Computer process simulation [72, 77, 83, 87, 95, 118, 129]; Agent based simulation [63] and a hybrid DES and ABS [81, 153] are proposed to improve healthcare operations. Demographic details of adult, female, and male patients [56, 68, 95, 102, 95, 147, 153] are used as variables to achieve patient characteristic for better analysis.
		Ambulatory care facilities	Organisation and management	0.49	Ambulatory care facilities	
		Organisation and management	Time factor	0.47	Outpatient	
		Ambulatory care facilities	Time factor	0.4	Time factor	
		Outpatient	Female	0.32	Adult	
					Female	
					Male	
					Waiting lists	
	Overbooking	Broken appointments	Failed appointments	0.67	Healthcare	This cluster investigates appointment scheduling [113, 119, 120, 122, 123, 134, 136] of healthcare [59, 118, 119] for walk-in [57, 65, 59, 93], scheduled arrival [64,92,113] and combination of scheduled and walk-in [135]. To manage no show, overbooking strategy was evaluated under different scenarios [60, 65, 95, 116, 118]. Broken appointment and failed appointment are common in health care [60,95] which causes underutilization of resources [60,57,116,118] and impact clinic operation efficiency [60,64]. Multiple server [119], and stochastic model [113] have also received considerable attention.
		Overbooking	No show	0.54	Appointment scheduling	
		No show	Server	0.25	No show	
		Healthcare	Overbooking	0.22	Broken appointment	
		Overbooking	Broken appointments	0.21	Failed appointment	
					Server	
					Scheduled arrival in service systems	
					Stochastic model in healthcare	

	Patient satisfaction	Quality-improvement Patient satisfaction Patient satisfaction Dynamic programming Patient satisfaction	Total quality management Quality improvement Total quality management Markov decision process Decision analysis	1 0.14 0.14 0.13 0.12	MDP Controlled study Total quality management Quality improvement Economics Process improvement Dynamic programming Decision analysis	This cluster reports alternatives for process improvement [61] such as centralized/decentralized service configurations [86], appointment scheduling with patient preferences [129], cancellation policy [60], fast track for non-urgent patient [79] to enhance patient satisfaction [72, 79, 116, 129] considering the economics/cost effectiveness [133]. Markov decision process [129] and adaptive dynamic programming [72] received considerable attention.
	Performance	Satisfaction Time Performance Performance Performance	Length of stay Physicians Physicians Length of stay Time	0.33 0.29 0.2 0.13 0.13	System Simulation optimization Length of stay Physicians Improve Satisfaction OR in health service	This cluster reports policies such as sequencing of patients [64], exam rooms assignment in outpatient care to reduce the length of stay [115, 117], waiting time [64, 75, 69, 82, 134], and physician idle time [115, 134] combined simulation-optimization approach which uses a heuristic to guide the search for an optimum for a discrete-event simulation model, combining the benefits of both is preferred.
Central and undeveloped	Algorithm	Walk-in patients Multi-agent optimisation Algorithm Walk-in patients Care	Real-time scheduling Algorithm Real-time scheduling Algorithm Algorithm	0.4 0.18 0.18 0.07 0.06	Hospital Health care delivery Ophthalmology Probability Walk-in patients Real-time scheduling Care Multi-agent optimisation	Research in this cluster describes the development of algorithms and evaluation of its performance for healthcare delivery. Improved patient scheduling algorithm [72, 122, 130,], meta-heuristics such as Genetic algorithm, Tabu search [69], hybrid ant-agent algorithm [152] have been developed. Application to the ophthalmic outpatient clinic [152, 122, 124, 98] has received considerable attention.

Peripheral and developed	orthopaedics	Economic evaluation	Orthopaedics	0.67	Costs Physiotherapy	Research in this cluster investigates cost/economic analysis of healthcare, especially orthopaedic [56,94,133] and physiotherapy-led orthopaedic clinics [56,133].
		Economic evaluation	Physiotherapy	0.67	Economic evaluation	
		Orthopaedics	Costs	0.67		
		Orthopaedics	Physiotherapy	0.44		
Peripheral and undeveloped	Model	Quality	Management	0.38	Waiting time Management	The use of collaborative models to improve the service quality and reduce waiting time [58, 74, 83, 81] is proposed in this cluster. Studies on diverting chronic disease patient flow from the emergency department [58] received attention.
		Model	Allocation	0.09	Emergency department	
		Waiting time	Model	0.08		
		Quality	Model	0.07	Allocation	
		Waiting time	Quality	0.07	quality	
	Discrete event simulation	Patient-flow	DES	0.12	Outpatient clinic	Using DES to model OPD issues such as patient flow [57, 67, 70, 73, 83, 82, 122, 125, 155, 61], capacity planning [57, 83, 154], appointment scheduling [93, 121, 126, 145], clinic planning[153], staffing [67,154], service planning [133], thereby improving the service delivery [82] and efficiency of service of healthcare[112], Specialized OPD such as ophthalmic [73, 122, 125] haematology [82 ,85, 111]; orthopaedic [133, 143] and oncology clinic [67, 82, 85, 121, 145] received attention.
		DOE	DES	0.11	Patient flow	
		Outpatient-clinic	Patient-flow	0.11	Service Design of experiment	
		DES	Outpatient-oncology-clinic	0.1	Mixed-integer programming	
		DES	Mixed-integer-programming	0.1	Outpatient oncology clinic Work sampling Delivery	
	Appointment systems	Appointment system	Optimisation	0.18	Scheduling optimisation	Research in this cluster focuses on appointment system schemes to find the best schedule for the patients [108, 119, 153] and medical equipment [116].
		Appointment system	Scheduling	0.11		

4.2.4 Cluster analysis for the sub-period 2014 to 2020:

Figure 8 shows the network of 9 clusters identified for 2014 to 2020 constructed using Pajek and INKscape. All the clusters associated with this period form primary clusters connected to more than one cluster. All the internal links of clusters are maintained, whereas external links with link weightage less than 0.12 are removed by using Pajek to improve the visualization. The central theme of this network is formed by cluster "Organization and Management" as it has more connections with other clusters. Table 8 shows the relationship between the clusters based on two measures: the number of links and the weight of links between the clusters. Cluster "Organization and management" has the most links with "patient satisfaction" and "algorithm". The average number of connections is found to be highest among cluster pair "Organization and Management" and "Patient Satisfaction". Maximum link weight and the average link weight is found to be high for cluster pair "Overbooking" and "Model", followed by "Model" and "performance". It is observed that the average link weight of the remaining cluster pairs is in the range of 0.12-0.18 as shown in Table 8. This suggests that the themes of these clusters are strongly associated and can be a future research direction, while the clusters "Overbooking" and "Performance" are the areas of ongoing research.

[Insert Figure 8: Links between clusters for the period of 2014-2020]

Table 8: Links between clusters for the sub-period 2014 to 2020

Cluster A	**Cluster B**	**No of links**		**Link weight**	
		Total	Average	Maximum	Average
Organization and management	Overbooking	3	0.04	0.22	0.17
	Performance	1	0.01	0.14	0.14
	Algorithm	6	0.07	0.23	0.15
	Patient satisfaction	17	0.21	0.23	0.16
	Model	1	0.02	0.14	0.14
	orthopaedics	3	0.08	0.18	0.15
Overbooking	Performance	3	0.04	0.18	0.14
	DES	2	0.03	0.19	0.17
	Model	3	0.06	0.33	0.22
	Appointment system	3	0.11	0.14	0.13
Model	Performance	5	0.09	0.25	0.18
	DES	1	0.02	0.14	0.14
	Patient satisfaction	1	0.02	0.13	0.13
Performance	Algorithm	1	0.01	0.16	0.16
Patient satisfaction	Algorithm	1	0.01	0.12	0.12
	orthopaedics	1	0.03	0.13	0.13
DES	Appointment system	1	0.04	0.13	0.13

5 CLASSIFICATION OF OPD LITERATURE

We undertook the full-text reading of the 161 articles, identified through a structured literature search process (Figure 1), to gain additional insights into the research domain, highlighting the OPD strategies (Section 5.1), performance measures (Section 5.2), and simulation approaches (Section 5.3) reported within the reviewed papers. We present the analysis for general outpatient departments (GOPD) and specialized outpatient departments (SOPD). Within SOPD, we classify the literature further based on SOPD specialization. There are 18 such specializations, namely, *emergency department, ultrasound, surgery, radiotherapy, radiology, primary care, paediatric, orthopaedic, ophthalmology, oncology, nephrology, internal medicine, haematology, gynaecology, gastroenterology, dermatology, dental and cardiology*. In the following sections, the literature classification for GOPD is presented in tables (9-14). SOPD classification, which is further sub-divided into specializations, is illustrated in figures (9-13). Both the tables and the figures include paper numbers in **[square brackets]**. **The supplementary data includes the mapping of the paper numbers to specific references.**

5.1 OPD strategy

Following Jun et al[6], the OPD strategies are broadly categorised as (1) *appointment scheduling*, (2) *patient flow/routing*, and (3) *resource allocation*. The strategies reported within reviewed articles in GOPD and SOPD are shown in Table 9 and Figure 9, respectively. Within GOPD, it is observed that *appointment scheduling* has received significant attention (36 papers; Table 9), followed by papers on patient flow (27 papers) and *resource allocation* (26 articles). Some of the papers may have adopted multiple OPD strategies. For example, paper [4] is classified under both *appointment scheduling* and *patient flow*. Within SOPD, *oncology* has received most attention (10 papers on *appointment scheduling*, 14 on *resource allocation* and 13 articles on *patient flow*; see Figure 9), followed by *ophthalmology*, *surgery* and *orthopaedic*.

Table 9: Strategies reported within reviewed articles in GOPD

OPD Strategy	General OPD
Appointment Scheduling	[4], [11], [13], [17], [34], [36], [37], [38], [39], [49], [50], [59], [64], [65], [71], [83], [84], [89], [92], [95], [102], [106], [108], [119], [120], [123], [129], [134], [135], [138], [139], [146], [150], [28], [1], [136]
Patient Flow	[4], [11], [13], [10], [24], [34], [40], [50], [55], [29], [83], [84], [86], [89], [108], [119], [134], [146], [28], [64], [65], [158], [1], [51], [132], [115], [148]
Resource Allocation	[11], [17], [24], [40], [49], [50], [52], [55], [59], [66], [83], [84], [86], [104], [123], [135], [154], [159], [28], [34], [39], [65], [92], [134], [139], [146]

[Insert Figure 9: Strategies reported within reviewed articles in SOPD]

(A) Appointment system: Following the work of Cayirli and Veral[4], the appointment system design decisions are classified into three decision levels as (1) *appointment rule*, (2) *patient type*, and (3) *adjustment policies* such as overbooking, same-day appointments, real-time scheduling, to reduce the disruptive effects of walk-ins, no-shows, and emergency patients. The appointment rule determines the slot for patients to reduce the waiting time. Appointment rules reported in the literature include IBFI (Individual block/fixed interval), OFFSET, DOME, 2BEG, MBFI (Multiple block/fixed interval), 2BGDM, MBDM [1]. Typically, patients are classified into manageable groups based on their arrival (new, follow-up, and transferred), age, sex (male, female), and physical mobility. Appointment system design decisions reported within reviewed articles in GOPD and SOPD are shown in Table 10 and Figure 10, respectively. It is observed that appointment rules and patient classification are reported in most reviewed articles. It is also observed from Figure 10 that overbooking has received significant attention in reducing the impacts of no-shows. Appointment scheduling policies have received significant research attention in the existing literature on OPD, while the complexity/uncertainty factors such as patient punctuality, appointment cancellation and walk-in that affect scheduling efficiency need to be considered as areas for future research.

Table 10: Appointment system design decisions reported within reviewed articles in GOPD

Appointment system design parameters	General OPD
Patient No show	[4], [10], [11], [13], [34], [38], [39], [50], [64], [65], [71], [89], [95], [102], [106], [119], [123]
Patient Unpunctuality	[11], [37], [64], [84], [89], [150]
Overbooking	[4], [39], [50], [65], [95], [119], [150]
Walk-ins	[38], [59], [64], [65], [71], [89], [106], [120], [135], [150]
Appointment Cancellation	[95], [106]
Appointment Rule	[11], [34], [38], [59], [64], [71], [89], [95], [108], [134], [135], [139], [146]
Patient Type	[24], [38], [34], [40], [50], [55], [64], [76], [89], [92], [106], [123], [134]

[Insert Figure 10: Appointment system design decisions reported within reviewed articles in SOPD]

(B) Patient flow/Routing: Patients in an outpatient clinic go through various medical services/pathways such as registration, pre-consultation, consultation, post consultation, payment, book appointments for the next visit before checkout. Information flow and patient flow are interrelated throughout patient pathways. Variation of services required by each patient and variation of each service duration complicate patient pathways and pose a challenge in ensuring optimal patient flow. Controlled patient flow can significantly reduce patient waiting time [130] and improve resource utilization [3]. To improve patient flow alternate pathways [40] [70], queue discipline [11], scheduling rule [27] [63] [65] and resource allocation [137] [27] [10] [115] [134] are proposed. From Table 11, it is identified that resource-based improvement has been used widely compared to pathway-based and scheduling-based improvements. Our analysis suggests that pathway-based patient flow (Table 11) such as directing patients on their arrival to optimal (operational) path using real time information such as electronic medical record (EMR) (Hribar et al[48]), hybrid Gen2IR/radio frequency identification (RFID) (Kato-Lin and Padman[49]), and RFID (Munavalli et al[50]) have not received much attention which supports the findings of Ahmadi-Javid et al[5].

Table 11: Classification of patient flow based on improvement techniques

Patient flow improvement techniques	General and Specialized OPD
Pathway based	[40], [70], [24], [156]
Scheduling based	[108], [146], [65], [63], [27], [60], [30], [57], [67], [109], [152], [73]
Resource Based	[134], [146], [10], [115], [137], [20], [27], [156], [30], [44], [112], [53], [57], [100], [91], [153], [41], [31], [127], [98]

(C) Resource allocation: Proper planning and allocation of resources such as beds, doctors, nurses, room, and equipment are essential to improve clinic performance such as waiting time, over time, congestion, and resource utilization. Healthcare services find it difficult to acquire more resources due to the rising cost [68], which identifies ways to improve the usage of existing resources [154]. The resource allocation reported within reviewed articles in GOPD and SOPD is shown in Table 12 and Figure 11. It is observed that studies on staff, doctors, and room allocation have received significant attention, while bed and equipment allocation decisions deserve further investigation. This is because the need for hospital beds is limited compared to inpatient care in ambulatory or outpatient settings. Within SOPD, equipment allocation decisions are reported in radiology, oncology, surgery, and gynecology departments. Typically, the purchase and maintenance costs of medical equipment such as MRI, CT scan, Ultrasound scanning are quite high [Du et al[51]]. Our findings suggest that equipment allocation decisions under multiple objective settings such as maximizing the equipment utilization while minimizing the patient waiting time need further study.

Table 12: Resource allocation reported within reviewed articles in GOPD

Resources Observed	General OPD
Bed	[21], [104], [154], [161]
Doctors	[34], [52], [134], [51], [148]
Staff	[28], [40], [55], [104], [123], [134], [154], [159], [51], [132], [148]
Room	[28], [55], [84], [146], [115], [132], [161]
Equipment	[17], [86]

[Insert Figure 11: Resource allocation reported within reviewed articles in SOPD]

5.2 OPD Performance Measures

The performance measures reported within reviewed articles in GOPD and SOPD are shown in Table 13 and Figure 12, respectively. Following the work of Cayilrli and Veral[4], the measures are classified as economic such as cost of resource [147,43, 107, 56], overall cost [147] cost of patient waiting time [64], cost of idle time [65, 73], cost of overtime [65], cost of no-show [46], inconvenience cost [16] and service-based that includes patient waiting time, length of stay, server idle time and over time [57], clinic throughput and quality. To reduce the waiting time, and the length of stay in the emergency department, low complexity patients are addressed to outpatient facilities (Fava et al[52]). Waiting time for health care are remains a major policy concern across different countries. A range of policy initiatives, including higher spending, waiting-times target schemes and incentive mechanisms, which reward higher levels of activity are used in different countries. (Siciliani et al[53]; Martin et al[54]). It is observed from Table 13 and Figure 12 that patient waiting time has received significant attention followed by server idle time/overtime while service quality improvement and throughput deserve further attention.

Table 13: Classification of GOPD with performance measures

Performance Parameters	General OPD
Cost	[28], [49], [50], [52], [55], [59], [64], [65], [66], [86], [96], [104], [134], [150
Patient waiting time	[10], [11], [13], [17], [24], [28], [34], [37], [38], [39], [40], [49], [50], [55], [59], [64], [65], [71], [76], [83], [84], [86], [89], [92], [95], [94], [108], [119], [120], [134], [135], [138], [139], [146], [150], [154], [158], [1], [51], [115], [132], [136], [148]]
Server idle time	[13], [37], [38], [39], [40], [59], [64], [65], [71], [119], [134], [1], [115], [136]
Server overtime	[11], [13], [34], [36], [38], [39], [50], [59], [64], [65], [71],[84], [119], [123], [134], [135], [146], [1], [136]
Length of stay	[24], [28], [29], [104], [146], [115], [148]
Clinic throughput	[4], [28], [55], [123]
Quality	[24] [83], [108]
Consultation time	[11], [17], [34], [36], [37], [64], [89], [120], [1], [136]
Number of patients	[4], [36], [38], [50], [95], [146], [150], [1], [51]

[Insert Figure 12: Classification of SOPD with performance measures]

5.3 Simulation Approaches used in OPD Research

The simulation approaches reported within reviewed articles in GOPD and SOPD are shown in Table 14 and Figure 13, respectively. The distribution of the simulation techniques reported in the reviewed papers is as follows: DES (67 papers), Simulation Optimization (58 papers), Hybrid simulation (3 papers), MCS (2 papers), ABS (1 paper), and SD (1 paper). Our result shows that DES is the commonly used approach in OPD operations. Articles have reported the use of process simulation using GPSS, H language [38], Java [21], business process model [76], virtual reality simulation [157]. Simulation optimisation used optimisation technique likes mixed-integer programming [122], algorithm [152], Markov decision process [56], mathematical model [16], stochastic model [113], goal programming [108] along with simulation.

It is observed that DES is used either alone or with queuing theory [105], process mining [138], CART analysis [126], and the design of experiments [73]. Simulation optimization is reported in 58 papers and illustrates the benefits of combining simulation with optimization. MCS and SD are the least reported simulation technique in OPD. MCS and SD are mainly suited to evaluate risk and healthcare policy at the macro level, respectively. ABS is typically used for modelling the behaviour of hospital entities (such as patients, doctors, and staff). The commonly used DES software within the reviewed articles includes *MedModel*, *Arena*, *Simul8*, *AweSim* and *AnyLogic*.

Table 14: Classification of different simulation techniques used in GOPD

Simulation Techniques	**General OPD**
Discrete Event Simulation	[64], [96], [138], [4], [28], [11], [24], [34], [40], [50], [52], [65], [84], [86], [104], [115], [135], [146], [148], [1]
Hybrid Simulation	[51], [55]
Monte Carlo Simulation	[66]
Simulation Optimisation	[123], [154], [49], [139], [71], [39], [92], [102], [106], [129], [132], [158], [10], [13], [37], [108], [150], [59], [119], [134]
Simulation	[95], [83], [76], [136], [38], [89], [17], [29], [36], [120], [159]

[Insert Figure 13: Classification of different simulation techniques used in SOPD]

6 CONCLUSION

Healthcare systems reported a growth in outpatient services due to patient preferences and clinical and technical advances (Abrams et al[2]). As OPD demand increases, meeting the demand for high-quality care within the limitations of resources and capacity remains an operational challenge. Computer modelling and simulation (M&S) approaches have also been widely used to model OPDs (Hong et al[1]) and experiment with strategies to improve metrics associated with effectiveness and efficiency. It is observed that there is a strong need to synthesize the existing literature on simulation modelling in OPD to identify important research themes that remained unexplored. The paper presents a comprehensive synthesis of the literature in computer simulation for modelling OPDs. It differs from existing reviews in that it employs bibliometric methods, along with a more traditional literature classification. A structured literature review approach was used to identify the 161 articles which served as the underlying dataset for both forms of analysis. While the bibliometric study relied on the meta-data from these articles and employed techniques such as keyword co-occurrence networks and cluster analysis, the literature classification of these articles was realised through full-text reading. In relation to the bibliometric analysis, following the works of Jose and Shanmugam[38] and Anandh et al[25], we categorise 161 articles into two sub-periods (2006-2013 and 2014-2020). Comparing these two sub-periods makes it possible to elicit how the research issues have evolved through the review period. Keyword co-occurrence network (KCON) and cluster analysis (Rajagopal et al[27], Allendoerfer[55], Leydesdorff & Welbers[56], Ronda-Pupo & Guerras-Martin[57]) identified ongoing and promising future research issues as a response to **RQ1** (*What are the significant and emerging research issues in general and specialized OPD?*).

To answer RQ2 (What are the commonly used performance measures in OPD, and how are they associated with the strategies used to improve performance?) and RQ3 (What are the commonly used simulation approaches to model OPD?), we employed the second form of analysis whereby we classified the same set of articles based on OPD strategy, OPD performance measures and simulation techniques. We further sub-divided the classification based on the source of the literature – namely, SOPD or GOPD – and the 18 SOPD specializations.

Based on the results of this bibliometric analysis, seven areas of possible research are identified. A detailed description of the seven perspectives presented below:

Patient flow: Patient flow management is multifaceted and driven by several internal and external key factors such as types of patients, levels of care required, the severity of patients, internal communication etc., (Gualandi et al[58]). Our analysis suggests that pathway-based patient flow [Table 11] such as directing patients on their arrival to optimal (operational) path using real-time information such as electronic medical record (EMR) (Hribar et al[48]), hybrid Gen2IR/radio frequency identification (RFID) (Kato-Lin and Padman[49]), and RFID (Munavalli et al[50]) have not received much attention. This supports the findings of Ahmadi-Javid et al[5]. Application of process mining technology in healthcare to discover the patient flow through EHR log data and then use it to build a simulation model is a promising future research. (Perimal-Lewis et al[59]; Rojas et al[60]). Similarly, integrating patient pathway optimization with appointment scheduling policies and resource/capacity allocation policies deserve further attention.

Equipment allocation decisions: Typically, the purchase and maintenance costs of medical equipment such as MRI, CT scan, and ultrasound scanning are quite high (Du et al[51]). Hence, the equipment allocation decisions within resource/capacity planning are significant as the unbalanced supply and demand of medical equipment affects both hospital revenue and patient satisfaction. A simulation model can be used to evaluate strategies to eliminate the bottlenecks, such as increasing the number of equipment (Viana et al[61], Parente et al[62]), versus optimizing the time slots for different patient types (Du et al[51]). Our findings suggest that equipment allocation decisions under multiple objective settings, such as maximizing the equipment utilization while minimizing the patient waiting time, need further study.

Patient unpunctuality, appointment cancellation, walk-in, and appointment rules: Appointment scheduling policies have received significant research attention in the existing literature on OPD, while the complexity/uncertainty factors that affect scheduling efficiencies, such as patient unpunctuality, appointment cancellation and walk-ins, need to be considered as future research. Patient unpunctuality is highly stochastic, leading to overcrowding and under or overutilization of resources. Appointment cancellations result in loss of productivity and revenue and reduced access to care due to the underutilization of appointment slots and resources. In outpatient clinics, regular walk-in patients who may fail to schedule an appointment are usually accepted and constitute a major stream of patients (Pan et al[63]). The random arrivals of walk-in patients significantly affect the service of appointment patients, increase physician overtime work and ultimately deteriorate service quality. Appointment scheduling policies that combine an appropriate appointment rule with the uncertainty factors mentioned above merit further research. It is also interesting to note that lateness of doctors and their interruption levels (i.e. gap times) have not been extensively studied within the reviewed OPD literature (Klassen and Yoogalingam[64]) as physicians' unpunctuality has less effect on patients' waiting times compared to the patients' unpunctuality (Aeenparast et al[65]).

Patient preference and cancellation policy: To enhance patient satisfaction levels and to mitigate the impacts of no-shows in OPD, researchers develop dynamic/adaptive appointment scheduling models incorporating patient preferences on the choice of physician, time slot and cancellation policy. To understand the impact of adding patient preference and cancellation policy on appointment scheduling, future research should focus on models and approaches that considers multi-preferences of patients and determine the time required for patients to call in advance for cancelling appointments.

Simulation based optimization: Simulation-based optimization (SBO) approaches in which outputs of a simulation e.g., DES, SD are inputs of an optimization approach (Yousefi et al[66], Golabian et al[67]) is a potential area of research for combinatorial resource allocation/capacity planning in OPD as it combines the benefits of both the approaches. A comprehensive survey on the optimization approaches and solution methods used in outpatient appointment systems is reported by Ahmadi-Javid et al[5].

Meta-heuristic algorithms: Modelling of OPD considering patient punctuality, patient preference, appointment cancellation, real-time walk-in, and capacity planning etc., is highly complex, challenging and often impossible to solve using exact optimization methods as they are NP-hard and stochastic. To obtain near-optimal solutions in short computation times, metaheuristic algorithms such as genetic algorithm (GA), particle swarm optimization (PSO), simulated annealing (SA), ant colony optimization (ACO) and tabu search etc. are being applied (Juan et al[68]). Combining metaheuristics with simulation to model the above issues is a highly recommended area of research in OPD services.

Service quality improvement and throughput: Our results suggest that most of the existing measures of OPD focus on patient waiting time followed by server idle time/overtime while other measures such as service quality improvement and throughput are seldom included. Our results align with a recent of review of Gualandi et al[58]. The service quality includes timeliness, efficiency, and patient centered care (Vahdat et al[69]). Designing outpatient clinics with a focus on improving the quality of the patient experience (such as minimizing the walking distance of patients and healthcare members) and operational efficiency deserve research attention. Similarly, maximizing patient throughput enhances the overall revenue. Effect of appointment policy, patient preference, cancellation, walk-ins on throughput deserve further research.

The limitation of the study is its reliance on Scopus and the Web of Science (WOS). Future studies could consider additional databases such as PubMed and Medline. However, it is arguable that a sub-set of the papers retrieved from the new databases would also be indexed in Scopus and WOS. For example, Scopus claims that approximately 4600 health science titles are indexed; it claims to include full coverage of MEDLINE (MEDLINE is the National Library of Medicine's premier bibliographic database) and Elsevier's comprehensive biomedical research database - EMBASE (Burnham et al[70]). Another limitation is the literature coverage; our study examined scholarly work from 2006 to 2020. Increasing the timeframe of analysis may result in numerous additional papers, and a detailed analysis would probably need to be conducted by a broader research term. There is also a technical limitation. The keyword co-occurrence network (KCON) presented in the paper is based on author keywords, keyword plus and index keywords. It is observed that certain index keywords, for example, "Article" and "Organization and Management", represented the clusters in KCON albeit they do not reflect the theme of the clusters directly because in SciMat a cluster is auto-labelled based on the name of the thematic network's most occurred keyword (Cobo et al[71]). Irrespective of the limitations, our review approach can be adapted for conducting methodological reviews of the literature that uses cluster analysis with the more conventional literature review.

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Appendix A: Calculation of Meyer's Index

The relative index of singularity (*Meyer's index*) is calculated to determine and compare the uniqueness or coverage of a given topic by the two databases. The greater the Meyer's index value, the more unique the database is (Fabregat-Aibar et al[33]).

The Meyer's index was calculated as follows:

$$\text{Meyer Index} = \frac{\sum articles\ x\ weight}{Total\ articles}$$

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$$\text{Scopus Meyer Index} = \frac{(68+(81\ \text{x}\ 0.5))}{161} = 0.673$$

$$\text{WoS Meyer Index} = \frac{(12+(81\ \text{x}\ 0.5))}{161} = 0.326$$

The results showed a higher singularity of Scopus with 67.3% of unique articles, while 32.6% of WoS records were unique. To measure the percentage coverage of one database over the other, the relative overlap was used as given below. Scopus covers 87.09% of the WOS, which justifies the use of both databases.

$$\%\text{Overlap Scopus} = 100\ \text{X}\ \frac{|Scopus \cap WoS|}{|Scopus|} = 100\ \text{X}\ \frac{81}{149} = 54.34\%$$

$$\%\text{Overlap WoS} = 100\ \text{X}\ \frac{|Scopus \cap WoS|}{|WoS|} = 100\ \text{X}\ \frac{81}{93} = 87.09\%$$

Appendix B: The list of 161 papers used for analysis

1. Cayirli, T., Veral, E., & Rosen, H. (2006). Designing appointment scheduling systems for ambulatory care services. Health Care Management Science, 9(1), 47–58.
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