Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 21s (2025)
https://www.jneonatalsurg.com

An Overview Of The Metrics Used In Appointment Scheduling Systems And Their Classification

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Cite this paper as: Rakesh Kumar Mishra, Geetanjali Sharma, (2025) An Overview Of The Metrics Used In Appointment Scheduling Systems And Their Classification. *Journal of Neonatal Surgery*, 14 (21s), 1342-1349.

ABSTRACT

In this Study are reviewed that are used to assess how well appointment scheduling systems performing. The English-language papers is searched from the The Google Scholar search engine and the PUBMED databases, WEB OF SCIENCE, SCOPUS, we classified assessment metrics based on queuing theory. Findings: 85 papers, for in-depth examination. We categories appointment scheduling system evaluation measures in addition to their definition and usage frequency. There are 24 measurements in all, with 12 (%50), 7 (%29), and 5 (%21) having to do with the arrivals (patient), clinic line (patient), and server (physician) categories, respectively. The majority of metrics is patient-related, which may emphasize how crucial the patient's viewpoint is when assessing appointment scheduling systems.

Keywords: *Evaluation Metrics, Queuing Theory, Ambulatory Care Facilities.*

1. INTRODUCTION

There are a lot of delays in healthcare. Most of us have to wait days or some weeks to schedule a treatment or an appointment with a doctor. We continue to wait to be seen. Patients frequently wait in the hallways of hospitals for beds, and delays in operation or examination testing are not common. A discrepancy between the capacity available to meet a service's demand and its actual demand leads to delays. This mismatch is typically transient and the result of inherent fluctuations in the time-of-service requests and the amount of time required to fulfil them. Since then, it has been used in a wide range of service industries, such as emergency response systems, Ala et al. (2023) analyzed the simulation appointment scheduling system (SASS) used in healthcare. Its main goal is to list the most important research subjects and draw attention to important scheduling challenges. Additionally, this critical evaluation aims to offer a thorough synopsis of these works, Alshammari, et al. (2024) analyzed; to create a prediction model for patient no-shows at the Saudi Arabian Ministry of National Guard Health-Affairs and assess how well different machine learning algorithms anticipate these occurrences. Apio et al, (2023) analyzed AI-based technology had the potential to completely transform healthcare, wellbeing, and life.AI-enabled technology is therefore permeating not merely every industry. of healthcare as well as our daily lives, and it must to be applied with a broad perspective that takes into account the entire range of people's lives. AI-based health technology has made a big difference in OPD workflow and wait times. Carreras et al. (2020) analyzed a comprehensive analysis is conducted about the forecasting of patient non-attendance. Of the publications on no-show prediction, 41 (or 82% of the total) had been published within the last ten years (and 32, or 64% of the total, over the last five years), demonstrating the problem's pertinence. Numerous variables that affect the findings reported in each of the research under consideration have been found by this review. These elements include the predictive model selection, the features these models employ, the variable selection, the framework for performance assessment, the imbalance between the classes and the performance measure, Cox et al. (2020) analyzed the simulation model with a variety of distributions (no-shows, walk-ins, service times, arrival times, external and internal time till appointment), as well as the current policies, behaviours, and presumptions. The model captures the bounds and restrictions of the available resources at this time, including the availability of doctors, nurses, and equipment, Graham et al. (2020) proposed a patient portal connected to an EMR revealed a significant reduction in the number of missed appointments, a self-reported drop in health system use, and pleasant patient experiences. Further qualitative and quantitative research is needed in Canada to examine the implications of the increased use of patient portals. Habibi et al. (2024) analyzed a grouping of appointment scheduling system evaluation criteria according to queueing theory nomenclature. The patient's perspective was crucial when assessing appointment scheduling systems, as evidenced by the fact that the majority of the metrics involved patients. It might be worthwhile to conduct more research given the correlation between the measures presented in the literature and their suitability for usage, Jeffin et al. (2022) proposed to five models with good accuracy for predicting patients' missed appointments in a clinic. several performance metrics, including F-measure, recall, accuracy, specificity, and precision; The precision-recall curve and receiver operating characteristic curve are used to assess how well various models operate, Ji et al. (2023) analyzed to the effectiveness of his suggested approach using a data set from the National Telemedicine Centre of China (NTCC) in conjunction with current techniques. Using textual data, they first demonstrate that his classifier can attain 90.4% AUC in a binary task. and then demonstrate how his approach performs better than the literature's stochastic model. Knight et al. (2024) proposed the data that is currently available demonstrates variation in the stages of AI and ML development as they relate to scheduling patients. Applications of AI and ML can help improve patient happiness, free up more time for clinicians, and eventually promote patient-directed healthcare and practice efficiency. These results contribute to the identification of new areas where AI platforms can be created to enhance patient scheduling. [Kasaie et al. (2023) analyzed to the problem of patients being late for appointments in mental health clinics and suggests using machine learning (ML) algorithms to forecast patient arrival trends with accuracy and support effective scheduling. To increase understanding and confidence in the algorithmic outcomes, four machine learning models multinomial logistic regression, decision trees, random forests, and artificial neural networks were created and contrasted using XAI methodologies. Researchers used three years' worth of appointment data from a mental health clinic to find numerous key variables that were associated with patients' tardiness, including as travel distance, appointment lead time, age, BMI, and specific mental health conditions, Niu et al. (2023) analysed the system's structural elements were initially introduced along with its features, system establishment procedure, and system decision-making framework. These are already-published literature study. After that, evaluated the methods used for AS system optimization and described the framework. Of these, the GA algorithm is the most often used optimization technique. Furthermore, a bibliometric study and discussion were conducted, revealing that the optimization of ASs has been increasingly concentrated on developing countries, which have demonstrated a greater interest in this sector than developed countries. Zheng et al. (2024) proposed by lowering no-show rates, improving scheduling effectiveness, and raising patient satisfaction, the implementation of DSS in hospital outpatient services seems to enhance operations management and the patient experience. However, further research is needed to fully understand how DSS affects outpatient waiting times. Patients who are younger and better educated are more likely to select DSS. The simplicity of use of the DSS is the primary factor that influences patient acceptance, which has improved in tandem with the progress of digital technology. More rigorously designed implementation studies are required to improve the accuracy of effect estimation. Qureshi et al, (2021) examined ten distinct algorithms using six different kinds of measurements. Additionally, they use their feature inclusion and data balance techniques to produce superior metric values. The review's findings confirm that there is only one statistic that isn't used to discuss model performance. The performance of the models has to be assessed using a variety of indicators. Srinivas et al. (2021) analysed how ML algorithms may be used to reliably anticipate regular clinical jobs like estimating consultation length and no-shows. These tasks can then be integrated into the clinical scheduling system to increase resource utilization and decrease patient waiting times.

Simsek et al (2020) analysis, a hybrid data mining-based methodology was developed to give medical decision-makers and healthcare organizations a patient-specific risk rating for no-shows. The comprehensive rising goal was to reduce the costs associated with patient no-shows and improve treatment by making better use of the resources that were available. Salazar & Yan et al (2021) examined the patient no-show categorization model and looked into the significant characteristics that indicate a patient won't show up for their planned visit. In order to get the desired results, they used certain machine learning approaches to determine the variables that would affect the patients' absenteeism and, most importantly, to forecast the possibility that any given patient would miss their planned sessions. Volk & Xie et al (2020) analysed Optimizing clinic availability and standardizing clinic sessions enhances patient satisfaction, creates new appointment opportunities, and boosts hospital income. Youn et al (2022) analyzed Healthcare planning and scheduling articles published in Production and Operations Management (POM) and other esteemed operations management publications during the previous three decades, highlighting popular subjects and outlining prospects for further study.Xie et al ,(2019) show how the hospital's deployment of a comprehensive reservation service for non-emergency registration reduced wait times, increased patient satisfaction, and successfully managed the outpatient demand. These findings showed that in a Chinese Grade 3A hospital, this approach produced the intended outcomes. Wu et al, (2021) analyzed, compared to the conventional approach, the WeChat calling system was substantially less expensive. Furthermore, the conventional calling system took a lot of time. The primary factor influencing OPD quality was longer wait times, which also led to disputes between patients and physicians.

In order to maximize hospital outpatient services, we hope that our systematic review will inspire additional high-quality research demonstrating the benefits of DSS and offer guidance for the creation of cutting-edge digital technologies. When deciding on the right number of employees, beds, and equipment as well as how to allocate resources and create new services, queuing models can be a very helpful tool. The continually rising costs and growing demand for healthcare put more strain on health care managers. There are numerous approaches to analyse the vast topic of health care. How can the optimal placements of hospitals and emergency vehicles be determined to give a certain population the greatest possible coverage of healthcare? If the overall distance between the locations and the hospitals needs to be less than a specific number, how many base locations of medical ambulances are required? How should radiation therapy be scheduled to minimize a cancer patient's treatment duration? In the worst-case situation, how might a trauma centre plan and reassign its nurses to ensure that the quality of care provided is sufficient? These kinds of issues need to be addressed in the health care industry, and operations research offers a variety of approaches and tools to accomplish so. With the use of mathematical modelling, the operational research model provides a methodical approach to issue solving and enables the characterization of an actual system's actions. A mathematical model-based strategy that effectively tackles issues in healthcare. One crucial job in the healthcare industry is managing the systems for making appointments. The initial premise of interaction between the medical facility and its patients and service providers is the appointment scheduling procedure as a result, the patient's impression and level of pleasure are directly impacted by this phase. As a result, improving productivity, care quality, and timely access are only a few advantages of assessing the appointment scheduling process In this study, we examine a number of assessment criteria that are used to gauge how well appointment scheduling systems are doing A general review of the popular assessment criteria of healthcare appointment scheduling systems is lacking, despite the domain of appointment scheduling systems receiving a lot of attention. This paper reviews and categorizes the metrics employed in the literature.

Material and Method: Bibliographies from a few selected papers is scanned. Every work on appointment scheduling systems, with the exclusion of review articles, letters and opinions, staff scheduling, and operating room scheduling, was examined. The assessment metrics is taken out of the chosen papers and classified utilizing the conventional nomenclature found in queuing theory.

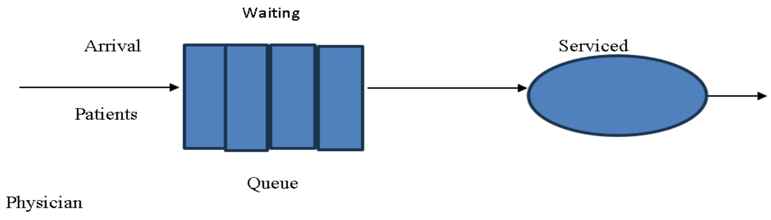

Fig 1: Queuing theory framework

System Structure of Appointment Schedule

Understanding the patient consultation procedure is a must before developing an AS system. As everyone is aware, those wishing to consult must show up as early as possible at the hospital outpatient clinic and proceed to the registration counter to receive a number. even if we use the online advance booking feature, we still need to report to the queue and wait according to the scheduled time. We have wait in the assigned viewing area after getting our number, and we have seen the doctor when we are called. Following the consultation, the patient might have to go through additional testing, and once the findings are in, they'll have to wait in line to see the doctor once more. The process flow for a patient's outpatient consultation in a clinical context is shown in Figure 2. The design of the AS system is seen as a collection of decision-making hierarchies, encompassing appointment regulations, patient categorization, and modifications to lessen the disruptive impact of no-shows. The patient might be required to undergo additional testing and reapply to the waiting list for a follow-up consultation with the physician following the results

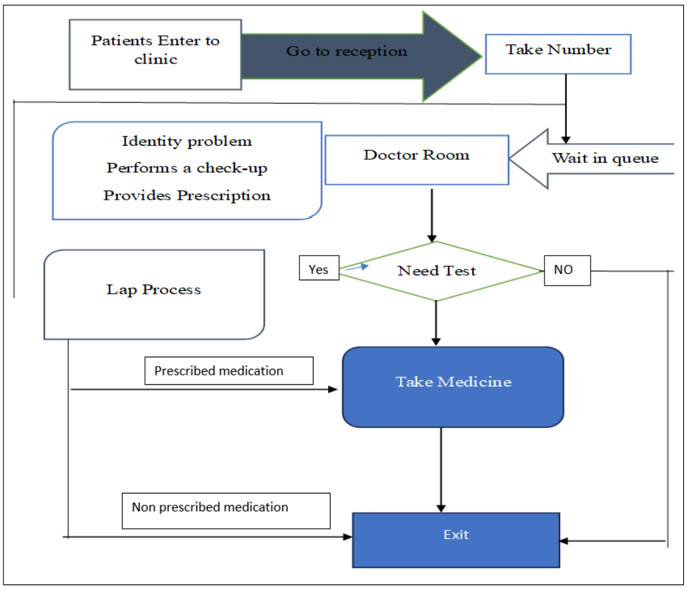

Fig 2: The flow structure of the patient in the hospitals

Result: 85 papers were ready for in-depth examination. The appointment scheduling system's assessment metrics are categorized in Table 1 along with their definition and usage frequency. (%48), Twelve metrics (%30), seven metrics and (%22) five metrics were associated arrival (patient) category, the clinic (queue), and the Doctors (server) category, respectively, based on this classification. Waiting times for patients in each category (%), rate of no-shows (%), and doctor idle time (%) the most often utilized measures

Table1: The categorization of appointment scheduling systems' assessment metric

Evaluation Matrics		**Definition**	**Frequency**
Arrival (Patients)	Patient absenteeism rate	The percentage of no shows divided by the total number of appointments maintained and the patients not showing up	27
	Patient satisfaction	Patient satisfaction in regard to making appointments	13
	Rate of non-attendance	Rate of cancellations plus no-shows	8
	Third time slot available for an appointment	The interval duration in which a patient's appointment request and the third available slot for a typical visit.	7
	Continuity of Patient Care	The percentage of patients who are able to see the doctor of their choice.	5
	Patient timeliness	The discrepancy in between the patient's scheduled arrival time and their precise time of arrival.	3
	Time of access	The duration in days between a request and an appointment.	3
	Walk-in percentage	The proportion of patients who arrive without an appointment out of every appointment.	2
	Rate of cancellations	The proportion of scheduled appointments that were postponed	2
	Rate of attendance	The percentage of patients who show up for their appointments on time compared to the total number of appointments	2
	Patient tardiness	Disturbance occurring between the patient's arrival time and the appointment time.	1
	Proportion of active patients	Interruptions that occur between the patient's arrival time and the appointment time	1
(Clinic) Queue Queue	Patient waiting time	Deduct the appointment or arrival time, whichever is larger, from the start of the service.	31
	Clinic size (Patient volume)	How many patients are expected for each clinic session.	4
	Patient throughput	The quantity of patients who arrive at the clinic, how many are checked out, and how many are discharged.	3
	Staff Satisfaction	Employee satisfaction with scheduling and appointments.	3
	Clinical Staff cost	Divide the entire salary of the clinical staff by the total number of visits.	2
	Acceptance rate	The proportion of appointments that are approved to the total number of requests for appointments	1
	Phone call Volume	Every call made during the whole workday at the clinic	1
Server	Doctor's downtime	Divide the entire idle time of the session by the total number of patients seen.	9

	Panel Size (Volume of Visits)	The total number of patients that the doctor is responsible	7
	Service time	How much time does the doctor spend with the patient?	5
	Physicians' Overtime	Dividing the total overtime by the total number of patients seen (actual session end time minus scheduled end time).	4
	Rate of utilization	The provider's actual service time divided by the total amount of labour time	2

Fig 3 represents the arrival pattern in the clinic. and the graph between the standard terminology in appointment schedule system in arrival (patients) and their frequency. Similarly, Fig 4 represents the Queue of patient in the clinic and the graph between standard terminology in queue in healthcare sector in appointment schedule system and their frequency. And Fig 5 represents the number of servers in the clinic and the graph between standard terminology used in server in appointment schedule system and their frequency in the hospital or clinic.

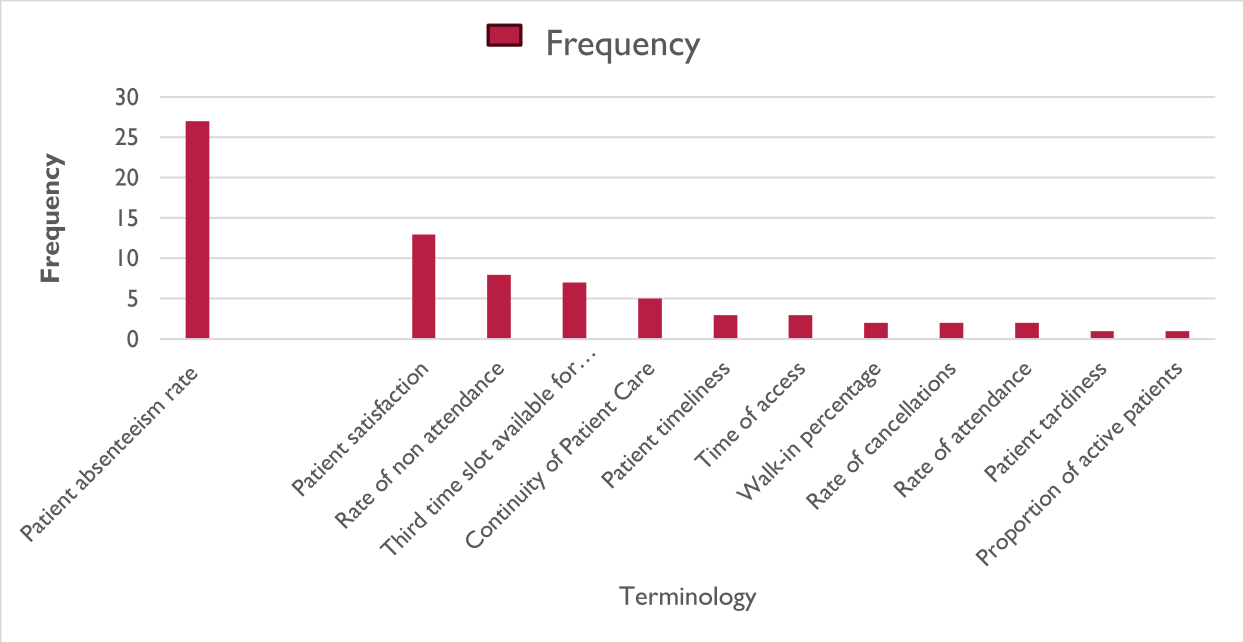

Fig 3: Arrival Pattern of Patient in the clinic

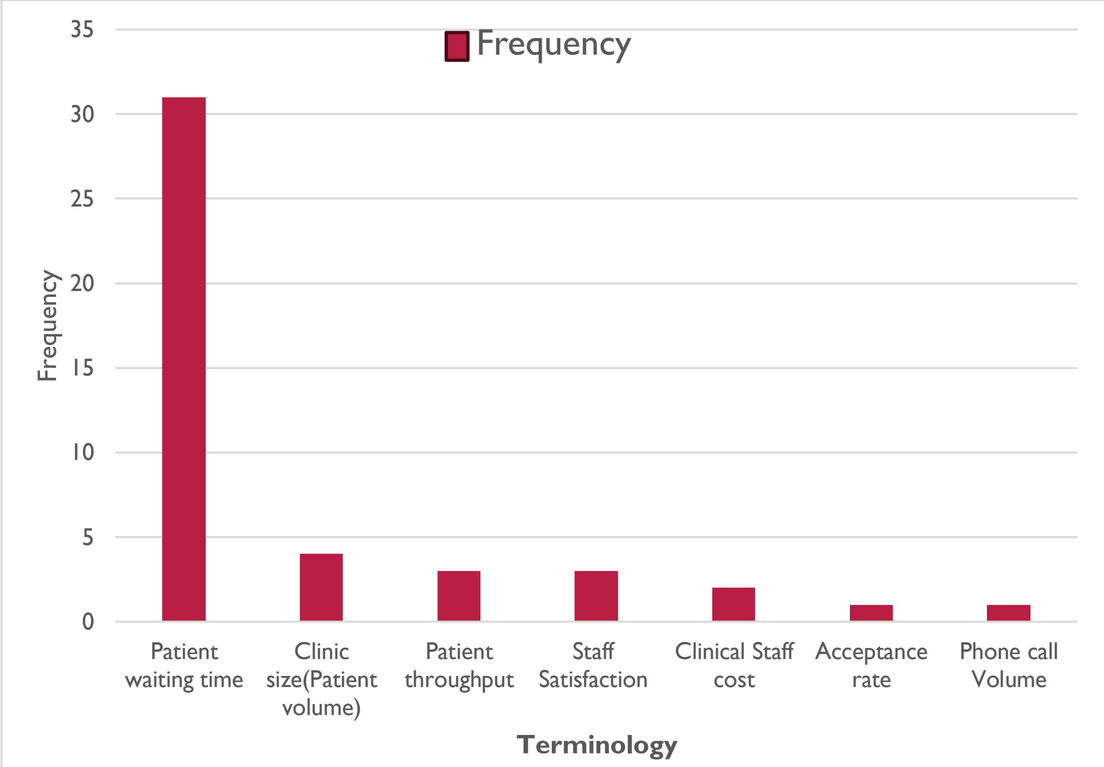

Fig 4: Queue of Patients in the clinic

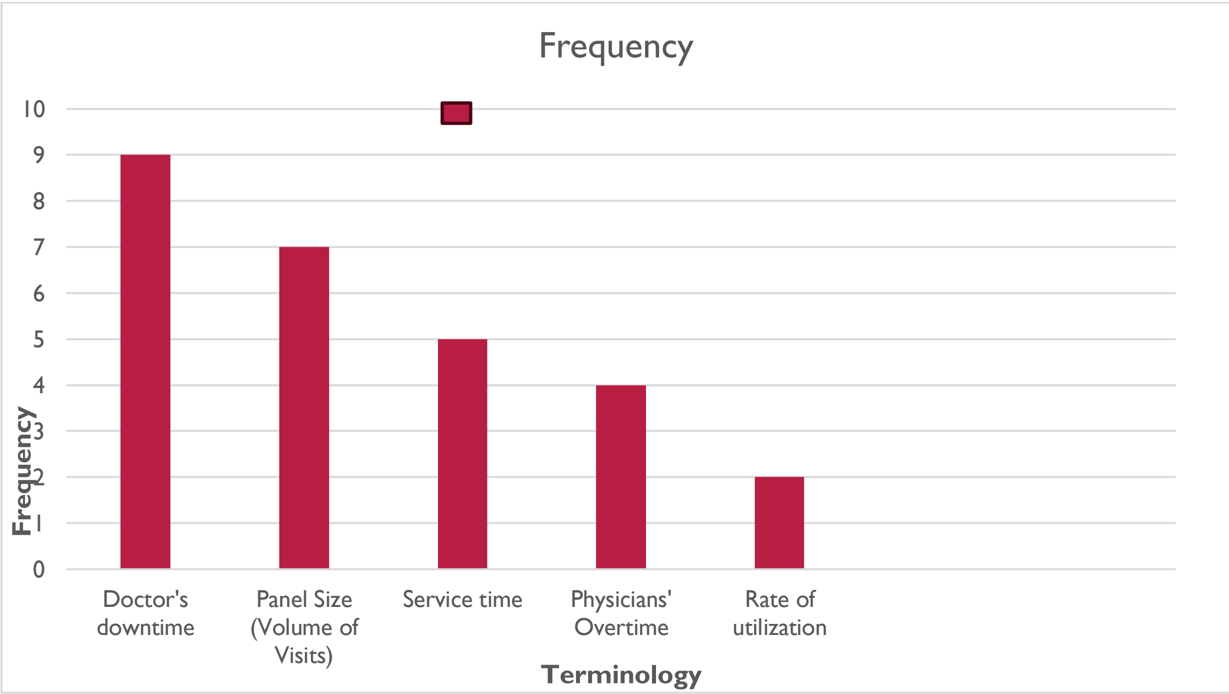

Fig 5: Number of servers in the clinic

Country and Publisher: Figure 6 represent the graph between number of country and number of research paper .we can easily see that China had published the most emphasis on the optimization technology as appointment schedule system (30 publications), the United States (25 publications), Canada (2 publications), England (5 publications), and Spain (5 publications), Japan (5), Australia (2 Publication),France (3 Publication), India (5 Publication), Russia (3 Publication), Notably, China has the greatest number of papers, demonstrating its strong emphasis on as optimization technologies. After that USA had the maximum emphasis on as optimization techniques which have been used. We can easily see that India has the minimum emphasis on as optimization techniques. for assessment on an appointment scheduling system. Similarly, Canada and Australia are also minimum used this standard terminology in appointment schedule system.

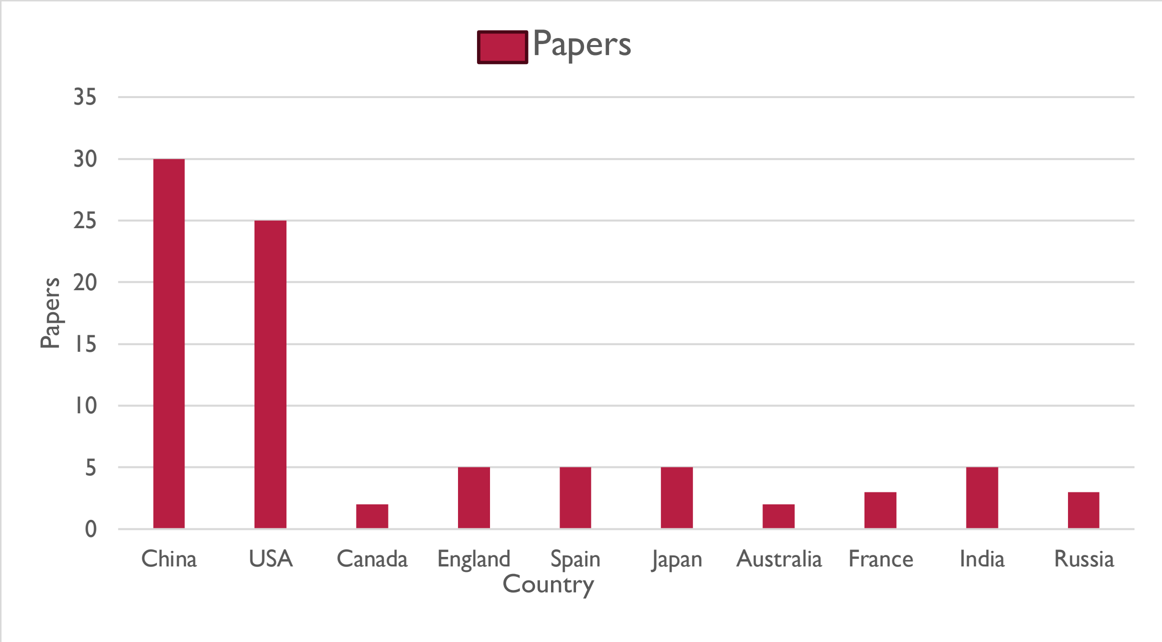

Fig 6: Number of Research Papers

Discussion: Using language from queuing theory, we categorized the most popular metrics for assessing appointment scheduling systems in this study. The majority of measurements is classified as arrivals (patients). This study's shortcoming is that we didn't look into whether a metric that was presented in research, the most pertinent one for the system's intended (clinical) usage.

Conclusion: Using language from queuing theory, we provided a taxonomy of assessment metrics for systems used to schedule appointment The majority of metrics is patient-related, which may emphasize how crucial the patient's viewpoint is when assessing appointment scheduling systems. and also, Future research will be warranted given the correlation between the metrics presented in the literature and their suitability for usage.

Acknowledgement: Thanks to Jaipur National University of Medical Sciences, the writers would like to acknowledge.

Author contribution: Each author read and approved the final paper after contributing to its design, data collection and analysis, and literature review.

Conflict of Interest: With reference to the publishing of this work, the authors have disclosed no conflicts of interest.

Financial Disclosure: With reference to the content of this work, no monetary concerns have been disclosed.

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