

Statistical Process Control: A Systematic Review of Control Chart in Healthcare Applications

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Abstract

Introduction: Statistical process control (SPC) charts are essential techniques to determine the root cause of mistakes, regardless of whether they come from unique or common factors. SPC charts in the medical field have become increasingly prevalent lately. Control charts are still a new concept to healthcare professionals, thus it's important to understand the difficulties involved in selecting and creating these charts for practical purposes.

Methods: The goals of this research are to provide a comprehensive review of the literature and give an example of the use and importance of SPC charts in the healthcare sector. Examining the suitability of articles obtained from various databases is the first step in this process, after which pertinent publications are screened and found.

Findings: 50 papers published between 2000 and 2024 were evaluated for title and abstract conformity out of an initial group of 300 articles. The four healthcare departments that make up the literature are pulmonary, epidemiology, surgery, and monitoring. Control charts were applied in seventeen different healthcare scenarios with twenty-one variables in various healthcare organizations. The bulk of the papers were published between 2011 and 2015, with a noticeable increase in volume following that year. As a result, commonly used control charts are P-charts, fuzzy charts, and CUSUM charts. This essay addresses the scope, assumptions, impacted factors, departments, nations, and limitations related to using control charts in various contexts.

Novelty and applications: This study presents the development and popularity of SPC charts since 2015 and offers an individual classification of their application in four healthcare departments. It presents fresh information for further investigation and application by providing a quantitative analysis of 50 experiments and outlining specific variables and outcomes affected by SPC processes. This comprehensive study adds a great deal to the body of information already in existence and provides insightful advice for using SPC charts in practice to improve quality control in the healthcare industry.

Keywords: Statistical process control charts, Healthcare departments, review of control charts, Variety of control charts, control charts applications

1. Introduction

Healthcare is getting better health by taking precautions for our bodies, detecting disease, aiding with health problems. Since the quality of healthcare is always a big concern^[1]. SPC charts are becoming more and more common in the healthcare industry, however prior studies have not always properly categorized how they are used in various sections of the industry. As such, our knowledge of their efficacy and implementation difficulties is still incomplete. Many healthcare professionals still find it difficult to choose and create control charts that are appropriate for particular healthcare situations. This is one of the current issues. In order to improve process monitoring and outcomes in the healthcare

industry, a thorough overview of the application of SPC charts is obtained through this research. The main objective of this paper to describe the concept of control charts and literature review to develop control charts in the medical field. Finding out if the articles that were obtained from various databases are eligible is the first step in a focused study. This is followed by screening and identification. Finally, 300 articles meeting the requirements recognized for identification. 50 papers published between 2000 and 2024 that met the inclusion control charts in healthcare departments found after publications screened solely on the basis of their title and abstract. To learn more about the topic, publications from highly influential journals were selected. This article was divided into departments

based on the output factors so those researchers were able to absorb its content. The literature survey demonstrates how control charts are used in different departments and nations wherever these research investigations have been performed is provided. Statistical part reveals the visual representations of the charts demonstrate how to choose the best kind of data and control charts for it, and how frequently these charts are utilized in the healthcare.

1.1 Research gap:

The current situation of the study on healthcare control charts indicates that further comprehensive studies are required. Control charts are acknowledged as useful techniques for observing and improving healthcare processes; still due to the wide scope of the healthcare industry, there is a lack of comprehensive research examining their efficacy in different healthcare settings. Many researches may be limited to a specific chart type or a specific topic related to control charts, or a selected group of situations. However, because it includes every aspect of the topic, this research has been extremely effective by comparing with others. The article describes the improvement and enhancement of this topic.

- What is the current scope of control chart applications in healthcare, and how widely are they used across different healthcare settings?
- What are the assumptions and limitations of control charts in healthcare?
- What criteria do researchers usually use to determine which material to include in a review?
- In healthcare settings, which types of studies use control charts, and which variables are most frequently monitored?
- Which control charts work best for which departments? Which nation conducted extensive research in this field, and which avenue of inquiry was expanded?
- Where could this field's research be strengthened, and what possibilities of investigation are available in the control chart on healthcare?

1.2 Statistical process control

Walter Shewhart created the SPC theory in 1920. It was created at the Bell Laboratory in the United States. The individual who made this theory well-

known across the globe is Dr. W. Edwards Deming. They noticed that different causes resulting from the procedure's repeated measurements would show variation. The process must be steady if the variation is expected. They ought to adhere to the distribution's lead. The variation in healthcare measurements is described by several types of distributions, which include binomial, Poisson, geometric, and normal...etc. SPC includes the control chart which is the most useful test. It is the procedure that effectively monitors hospital characteristics including the death rate, the number of infected patients, the waiting period, etc. It serves as a tool for observing and minimizing the variability in quality features.

1.3 Control charts

The control charts have two halves of the measurement series, each with three lines. The middle line represents the average of the measurements. Usually, the values of UCL and LCL are calculated from the difference of the actual variability in the data. Gaurav Suman^[2] describe that these control charts are utilized in the healthcare industry to decide on shifts and enhance their quality for patients. They assess their treatment-related shortcomings and work to make improvements. It is an excellent process monitoring approach to identify the unwanted variability and sample plots are situated outside. Although it does not completely remove variability, it does contribute to its reduction. Any process cannot be kept under control for an extended period. They are not stable forever, and the assignable cause will appear randomly, leading to the variability that leads the process out of control. To evaluate the effectiveness of the control chart, hypothesis testing is useful. Type-I -The likelihood of a type-I error is viewed as being out of control while the procedure is actually in control. Type-II – vice versa. Many kinds of control charts can be used in various situations. According to Shewhart^[3] there are three sigma limits for action and two sigma limits for warning. Usually, the traditional control charts are called Shewhart control charts. The process isn't working properly if the point is between the warning and the control boundaries. It is necessary to take action to speed up the procedure. The sensitivity can be increased and the shift can be detected sooner by using warning limits. The

sampling frequency and sample size must be considered when designing the control chart. Large samples can detect minor shifts in the process. An additional method for calculating the sample size and sampling frequency is to compute the average run length of the control chart. ARL is used to show how effectively the control charts perform. The capability of the process is comprehensible with the help of control charts. The control limits are if w is the sample statistic of the quality features, the mean of w is μ_w and the standard deviation is $\sigma_{\bar{x}}$ then the control limits are

$$UCL = \mu_w + L\sigma_{\bar{x}}$$

$$CL = \mu_w$$

$$LCL = \mu_w - L\sigma_{\bar{x}}$$

The control charts have two phases of applications. Phase I of the process includes data collection, analysis, and the construction of control limits to indicate whether the process is under control or not. Phase-II stage is used to monitor the process and set control limits by comparing the sample data for each repeated sample. Typically, the control chart's performance is estimated using the average run length. However, in Phase II, Shewhart control charts fail to effectively detect small to moderate-size shifts, the ARL performance is bad. Now, they utilize the sensitizing rules to make the charts more sensitive.

To increase the sensitivity of control charts, they create the sensitizing rules. By using these rules the minor shifts determined easily. The first four rules are known as Western electric rules.

The rules are

- Either one point or additional points lies outside the three-sigma limits of control charts.
- Dual out of three repeated points lie outside the warning limits (two sigma limits) however they lie inside the control limits.
- Quarter out of five repeated points lie far away from one sigma limits of control charts.
- A loop of eight repeated points lies on one of the center lines.
- If a row has six points increasing or decreasing steadily.
- If there are fifteen repeated points in Zone C, both above and below the center line.
- No points in zone C and the eight repeated points on both sides of the centerline.

- Alternating up and down fourteen repeated points.
- Non-random and not usual patterns in the data.
- The warning or control limits have one or more points.

There are two kinds of control charts based on the sorts of data: control charts for variables and control charts for attributes. For univariate cases, shewhart control charts are employed. Variable control charts for numeric variables; X bar chart-used to measure the process mean, Range chart-used to measure the range, Sigma chart- used to measure the standard deviation. Attribute control charts for non-measurable defect, the charts are np chart - used to find non-conforming, p chart- used to find the fraction nonconforming, h chart- used to find the average number of events, g chart- used to find the total number of events, c chart-used to find the total number of non-conformities,u chart- used to find the average number of non-conformities. To establish the use of c chart for count data we will create an example the weekly number of hospital acquired pressure ulcers at a hospital that, on average, has 200 patients with an average length of stay of five days.

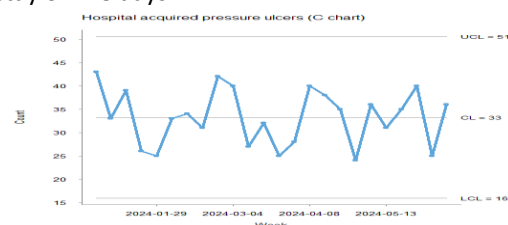


Figure1. c chart for healthcare data

Time weighted control chart determines the shifts; usually it gives more weight to recent data points, reflecting the idea that recent observations may be more indicative of the current state of a process. EWMA charts can be altered to show any size shift in the process. The cumulative sum control chart (CUSUM) was first proposed by Page in 1954. Classic control charts typically function best when the magnitude of the change is more than 1.5; smaller shifts have little bearing. Shorter shifts are better served by cusum charts. By showing the cumulative total of the sample values as they move away from a desired value, it instantly presents all the data in the series of sample values. Time series control charts are used to monitor a process over time by plotting data points in chronological order. ARIMA control charts based on

the residuals (errors) obtained from an ARIMA model to monitor the behavior of the forecasting errors and identify any unusual patterns.

Multivariate control charts are effective for large number of process variables. Chi-square control charts used for chi square distribution with two quality characters. Multivariate exponentially weighted moving average is similar to the EWMA. The purpose of the Hotelling T^2 control chart is to identify changes in the average of multiple connected variables.

Fuzzy set theory is usually used to describe uncertainty and inaccuracy. The parameters are fuzzied and combined with control charts to get better results called fuzzy control charts. Use this fuzzy theory to control charts to get more accurate control charts. These charts are extra sensitive than traditional control charts. Fuzzy control charts also give better results for healthcare.

1.4 Benefits of control charts:

The articles selected list a number of advantages of using control charts. Initially charts are said to be easily understood visually and have the potential to provide insights that would not otherwise be possible. They can show if a process is stable or unstable and offer a way to evaluate the behaviour of a process in steady state. Simple statistics are used in control charts to measure impacts over time. They enable the identification of a shift in performance, whether gradual or unexpected, and offer early notice of systemic change occurring in a process. When used in process analysis, control charts can greatly enhance the quality of time-sensitive processes.

2. Objectives

The purpose of this study is to offer recommendations for the application of control charts in the medical field. This paper aims to explain control charts scope, applications, benefits, limitations, assumptions, and drawbacks. The literature review provides guidance on selecting a paper, and the context and details of the chosen paper are displayed. A statistical analysis reveals how frequently these charts are utilized in the medical field.

3. Methods

Review methodology:

The main approach of this review article is to recognize the use of control charts and evaluate a field's contribution. The author conducted a specific literature search in the relevant databases to find studies that met the inclusion criteria.

3.1 Eligibility criteria:

Control charts are frequently used in the healthcare sector to monitor procedures involving patient care, patient safety, infection control, drug delivery, and other quality improvement projects. Different techniques from various studies are presented and descriptively addressed. The first stage is to choose the topic; the criteria for inclusion of review article should be "Control charts in healthcare".

3.2 Study identification

A search of John Wiley, Elsevier, Taylor & Francis, BMJ, Springer, internal journals Scopus, Google scholar, science direct, Medline, etc... was performed to identify the various types of control charts in healthcare for all the year to date (2024). To ensure that the research quality is trustworthy, every scientific source in the second point is classified as minimum level and published in a peer-reviewed journal. The literature review in this study will merely be one of its limitations. Published articles between the years 2000 and 2024, and they must be written in English. Examining the papers' abstracts and titles for relevancy is the first step in the article pre-assessment process. The specific terms are shown in the Figure.2, like control charts, control charts for healthcare, variable control charts for healthcare, attribute control charts for healthcare, and fuzzy control charts for healthcare, Time weighted control charts in healthcare, Time series control charts in healthcare, applications of multivariate control charts in healthcare. When conducting the research, the title and abstract were very important in determining whether the paper would be further included in the review. The key issues of the research paper are to be summarized in a conclusion, enabling readers to understand information more clearly.

3.3 Study selection and data extraction

Limiting the evaluation to the first 300 articles discovered by the general scientific search engine is another method to lower the quantity of articles that need to be reviewed in this initial phase.

Usually, this machine displays search results in an ordered manner according to their relevancy. A total of 300 items are produced by this preliminary procedure. From all 300 articles, only 100 articles filtered on the basis of primary eligibility. Due to issues in implementations, 30 articles were removed. For all 70 articles, a final quality assessment is conducted (see Figure.3). For selection, the title and abstract of the study were reviewed to identify with the content and determine whether the article met the inclusion criteria. In addition, the team lacks the ability to access ten articles, which results in an additional decrease in the overall quantity of articles. Some irrelevant papers are removed; relevant papers were included. There are now just 50 articles remaining from the prior number of assessments shown in the Figure.3. We examine all included articles and extracted and organized information relevant to this review. Table with title, author, and year of publication, inclusion criteria, and purpose of the study, results, journal, and types of control charts used in SPC chart.

Type of chart	Subgroup size	Distribution of data
X bar and R chart	$1 < n < 10$	Normal (Gaussian)
X bar and S chart	$n > 10$	
I-MR chart	$n = 1$	
np chart	Constant sample size with defectives	Binomial
p chart	No constant sample size with defectives	
c chart	Constant opportunity with defects	Poisson
u chart	No constant opportunity with defects	
g chart	The number of units or observations within each subgroup.	Geometric

h chart	The number of units or observations within each subgroup.	
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Table 1. Appropriate use of charts



Figure 2. Study identification words

4. Results and discussion

A survey of the literature done for this study reveals various attempts to include the actual nature of health care into the monitoring procedure. Different an efficient monitoring tool is created but the results of control charts are more efficient. In light of this finding, we attempt to make a literature review on control charts. The literature review is segmented based on the healthcare departments. Five departments (Emergency, Surgery, Epidemiology, Pulmonary and Monitoring) yielded forty studies. The information about the research papers that are included is tabulated and displays the type of study, nation, variables used, types of charts, and details of the work completed.

4.1 Study done in Emergency department:

Emergency department deals with waiting time, pulse, mortality, accident, etc. Therefore, there's always room for improvement in the emergency department. The work done, chart types, variables used, research types, nation, and names and years of the authors are all displayed in **Table 2**. There five articles have been included for emergency department [4,5,6,7,8]. From Table.2 Time weighted control charts play an essential role for emergency department.

4.2 Study done in Surgery department:

The surgery department frequently has too many mistakes and inefficiencies like surgery, cardiac

patients, postpartum, knee replacement. The work done, chart types, variables used, research types, nation, and names and years of the authors are all displayed in **Table 3**. There are nine articles have been included for surgery department [9,10,11,12,13,14,15,16]. From Table.3, risk adjustment control charts, p chart have been used for surgeries.

4.3 Study done by Epidemiology department:

To put it simply, infections linked to certain diseases or medical conditions are handled by this department. Attribute control charts plays an essential role in epidemiology department. The work done, chart types, variables used, research types, nation, and names and years of the authors are all displayed in **Table 4**. There are ten articles have been included for epidemiology department [17,18,19,20,21,22,23,24,25,26]. Various types of control charts used in epidemiology department.

4.4 Study done by pulmonary department:

Pulmonary medicine is the area of study that focuses on the causes, identification, management, and prevention of diseases. **Table 5** includes the names and years of the authors along with the specifics of the work completed, chart styles, variables used, research types, and country. The pulmonary section has comprised two sets of studies. There twelve articles have been included for pulmonary department [27,28,29,30,31,32,,33,,34,35,36,37,38]. Each variable has different control charts.

4.5 Study done by Monitoring department:

Monitoring area focus on the diseases like diabetes, blood pressure, bone narrow, bacteria. **Table 6** includes the names and years of the authors along with the specifics of the work completed, chart styles, variables used, research types, and country. Various control charts are used for monitoring. There are ten articles have been included for monitoring department [39,40,41,42,43,44,45,46,47,48].

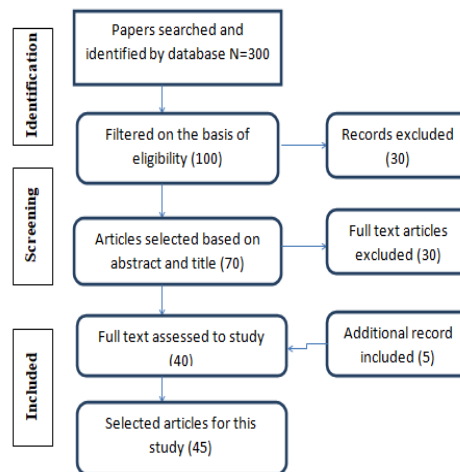


Figure 3.Flow charts

As started with 50 appropriate articles out of 300 potentially relevant searched articles have been identified for the study. In general, statistical analysis is the process of gathering, analyzing, and interpreting quantitative data to identify patterns, connections, and fundamental reasons. For the statistical analysis, bar charts are used. Study analyses are divided into the following subsections.

4.6 Results and findings:

The study includes various articles from various time periods. Figure.4 shows the quantity of research chosen from various nations. Research for 13 of the articles was conducted in the U.S.A^[7,11,14,16,17,20,24,28,29,30,39,45]. Four articles selected from U.K^[4, 6, 21, 22] and Iran^[31, 33, 34, 46]. One or more articles from Austria, Brazil, Coimbra, Denmark France, French, Germany, Greece, India, Iris, more than 25 countries included in this study. From the bar plot (See Figure.4) the majority of research on the use of control charts in healthcare is conducted in U.S.A. Figure 5 illustrates the variation in the number of studies included from various years; there are more publications in the years 2010 and 2015. The earliest study takes from 1998 and latest to 2024, since there is a publication gap between from 2000 to 2005 and 2010-2015. From 2015 they become more frequent. Also, Figure 5 illustrates number of studies includes various charts, most of them about CUSUM^[4, 7, 15, 21, 48] and fuzzy control charts^[31,32,33,34,35], indicating their greater utility in the medical field. Figure 6 shows the numbers of the various study areas are represented by the years. We have more articles from pulmonary department.

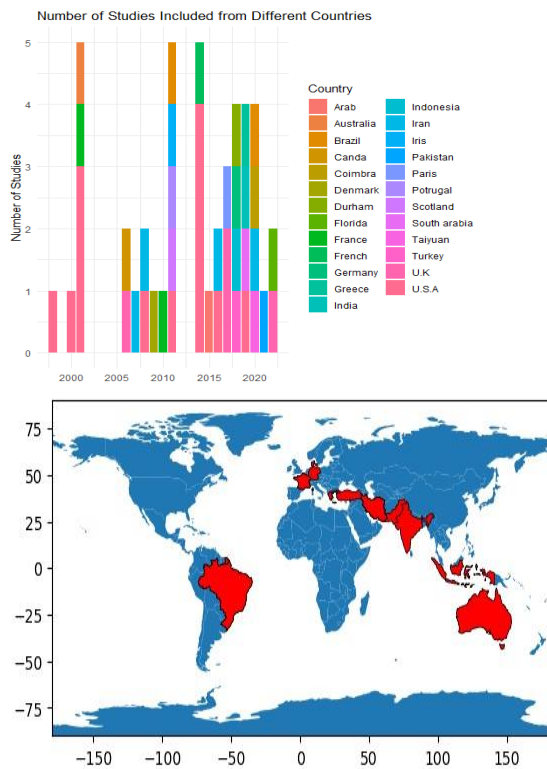


Figure 4. Number of studies included from different countries

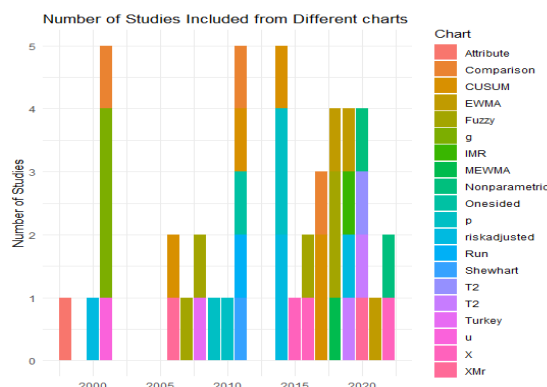


Figure 5. Number of studies includes various years and charts

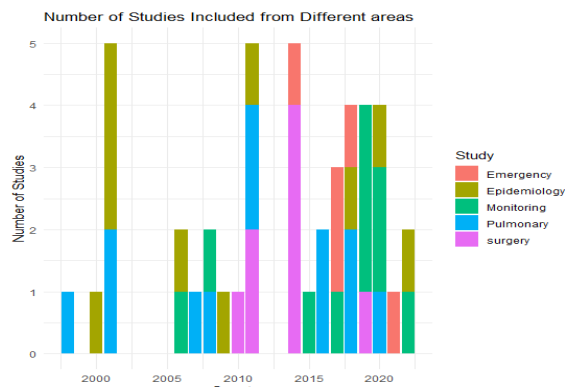


Figure 6. Number of studies included from different areas

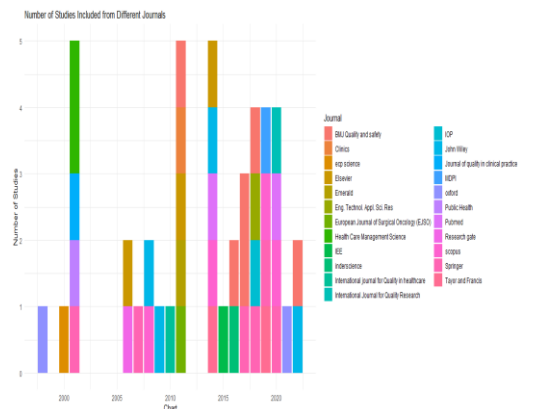


Figure 7. Types of journals included for the study

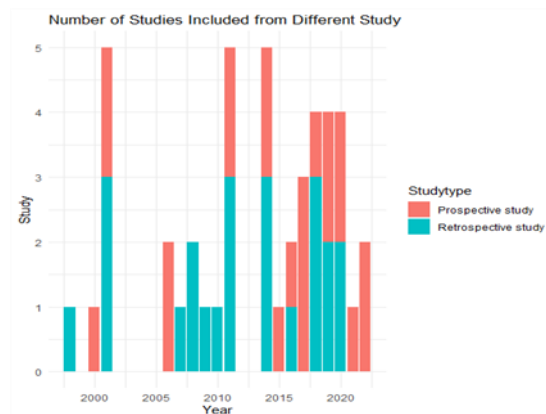


Figure 8. Included types of study

From the above bar chart, Figure.6 shows the types of charts used in various departments in healthcare. It reveals that the fuzzy control charts plays an important role in pulmonary department and p chart also popularly used for surgery department. From the bar chart we can easily get knowledge about control charts use in healthcare department. Figure 7 shows the list of journals which are taken for this study. The majority of the articles are taken from the highly impacted journal like Taylor & Francis and Springer journals.

Table 2. Literature survey on Emergency department

Chart Type	Output variable	Author	Country	Study
CUSUM [4]	Mortality	Jenny Neuberger et al	U.K	Prospective study
MEWMA [5]	Pulse	Hongxia Zhang et al	German	Retrospective study

Comparison [6]	Mortality	Biau. D, et al	U.K	Retrospective study
CUSUM [7]	accident	Anna Schu h, et al	U.S. A	Prospective study
X-Mr [8]	Waiting time	Nayara Nicol e de Sene Pereira	Brazil	Retrospective study

Figure.8 demonstrates the retrospective and longitudinal study kinds. The figure makes it evident that retrospective studies account for the majority of research output. The distribution of number studies from 2000 to 2024 is displayed in a box plot. The figure illustrates the distribution of research numbers in various nations across the timeline, as well as the number of studies in various chart kinds, journals and study type, etc. R software and python software were used for this analysis part.

The output variables that were employed differed significantly. The most frequently used variable is treatment [28,30,31,32,33,34,35,36,37] and infection [17, 20, 23, 24, 25, 26]. The remaining variables like diabetes, blood pressure, cardiac patients, waiting time, mortality, pulse, cancer, etc. more than 25 variables are used one or two times. With regard to content Table 3, Table 4, Table 5, Table 6 condenses the research context, output variables, study type, chart type, country.

Table 3.Literature survey on Surgery department.

Chart Type	Output variable	Author	Country	Study
Shewhart control charts [9]	Ceserian delivery	Michael J. Turner	Iris	Ceserian delivery
p chart [10]	Surgery	Antoine duclos, et al	France	Retrospective study

Risk adjusted control chart [11]	Surgery	Fatemeh Mohamadian	U.S.A	Prospective study
Risk adjusted control chart [12]	Surgery	Athanasios Sachlas	Greece	Retrospective study
p chart [13]	Postpartum	Dupont, COccellier, et al	France	Prospective study
p chart [14]	Cardiac patients	Amitava Mitra	U.S.A	Retrospective study
CUSUM [15]	Cardiac patients	G.S.Collin, et al	Scotland	Prospective study
Risk adjusted control chart [16]	Knee replacement	Mahiben Maruthappu et al	U.S.A	Retrospective study

Table 4. Literature survey on Epidemiology

Chart	Output	Author	Country	Study
g chart [17]	Infections	James C. Benneyan	U.S.A	Prospective study
p chart [18]	Thyroid	A. uclos, et al	Denmark	Retrospective study
Non parametric control chart [19]	Breast cancer	Jin Yue., et al	Coimbra	Prospective study
risk adjusted	Infections	Tracy L. Gustafson MD	U.S.A	Prospective study

control chart [20]				
CUSUM [21]	Congenital malformation	Sego, L. H.	U.K	Prospective study
X bar [22]	Disorder	Hilary McFaul et al	U.K	Prospective study
EWM A [23]	Infections	Arthur W Baker, et al	Durham	Prospective study
g type [24]	Infections	James C. Benneyen	U.S. A	Prospective study
Comparison [25]	Infections	IsabelCristinaGomes, et al	Brazil	Prospective study
Comparison [26]	Infections	Anthony P Morton et al	Australia	Retrospective study

Time weighted charts are being used more often in clinical settings for Emergency department. [4] Four control charts for binary clinical performance data were compared, and the results showed that performance varied depending on the situation. While the CUSUM performed exceptionally well in detecting small increases, than other charts. Despite being intended for low event rates, the g-chart performed less well than the CUSUM. These results emphasize how crucial it is to choose suitable control charts depending on the degree of rate variations. By using MEWMA time weighted charts [5] deviations are quickly identified by using principal component testing and examining the factors determines the optimize treatment time and resource allocation by identifying abnormalities before they become serious problems. There is a lack of clarification in the literature regarding the use of CUSUM in surgical and interventional procedures, which causes uncertainty. This impact produce lot of retrospective reviews, [6] this evaluates thirty-one pertinent researches, pointing up differences in

CUSUM implementation and reporting. The main conclusions show that before CUSUM reporting is widely adopted in subsequent research, it needs to be clarified and standardized. This study [7] illustrates how shorter aggregation periods result in the prompt discovery of increased accident frequency by comparing Poisson and exponential CUSUM plots. The Control chart [8] for Individual Measurements and Moving Range was used to track the length of time patients waited, and the Y-index was then used to assess the service's capabilities. Based on the Process Capability Index (Path=-0.15) and the average wait time of 121.88 minutes for a doctor's appointment, that the service is inefficient.

Table 5. Literature survey on Pulmonary

Chart	Output	Author	Country	Study
One-sided charts [27]	BMI	Florabela Correia, et al	Portugal	Retrospective study
Run chart [28]	Treatment	Rocco J Perla, et al	U.S. A	Retrospective study
X bar [29]	Admission	Kathleen Brown, et al	U.S. A	Retrospective study
Attribute control chart [30]	Treatment	James C. Benneyan	U.S. A	Retrospective study
Fuzzy control charts [31]	Treatment	AlirezaFaraz M. et al	Iran	Retrospective study
Fuzzy control charts [32]	Treatment	Nilufer Pekin Alakoc. et al	Turkey	Retrospective study
Fuzzy control charts [33]	Treatment	Azam Moraditadi,etal	Iran	Prospective study
Fuzzy control	Treatment	V. Amirzadeh,	Iran	Retrospective study

charts[34]				
Fuzzy control charts [35]	Treatment	Wibawati, Muhammad et al	Indonesia	Retrospective study
g chart [36]	Treatment	Park, C, et al	Korea	Retrospective study
u chart [37]	Treatment	T Hanslik, et al	France	Retrospective study
EWMA [38]	Coronavirus	Yasar Mahmood, et al	Pakistan	Prospective study

[45]		Torng et al		e study
Hotelling T ² control chart [46]	Bone narrow	MahmoodShahra bi et al	Iran	Retrospective study
X bar [47]	Blood pressure	Tamador Albloushi, et al	Arab	Prospective study
CUSUM [48]	Amr bacteria	L. Righi,et al	Paris	Prospective study

Table 6. Literature survey on Monitoring

Chart	Output	Author	Country	Study
I-MR control charts [39]	Diabetic patients	FatmaPakdil, et al.	U.S.A	Prospective study
EWMA [40]	Diabetic patients	Muhammad Aslam et al	South Arabia	Prospective study
Non parametric controlChart [41]	Blood pressure	Linli Tang	Florida	Prospective study
Hotelling T ² control chart [42]	Neutrophilic	SarithaM .B,et al	India	Retrospective study
X-Mr [43]	Asthma	FazelHayati, et al	Canada	Prospective study
Hotelling T ² control chart [44]	Bone narrow	Chen-Mao.Liao ,et al	Taiwan	Prospective study
Turkey's control chart	Monitoring	Chau-Chen	U.S.A	Retrospective

A Shewhart control chart plays a vital role in Surgery department. P-charts promote patient safety in healthcare settings and aid in ongoing quality improvement initiatives by fusing time series analysis with graphical data presentation. Quality control performance charts make it easier to identify institutions that need an obstetric practice examination by analyzing national caesarean rates. [9] The effectiveness of control charts for caesarean rates in 19 Iris maternity hospitals is assessed in this article. The significance and application of p-charts for adverse event monitoring in clinical practice are explained in this study [10]. It describes the essential components for creating, interpreting, integrating into practice, and reporting research p-charts. [11] Over a seven-year period, this observational study from a French maternity centre in the Rhône-Alpes area uses statistical process P-charts to show a considerable drop in the occurrence of severe postpartum hemorrhage following vaginal delivery. Effective management leadership and a culture of constructive assessment are crucial for the implementation of p-charts and continuous quality improvement in departments. In order to track patient survival rates following surgery, a novel risk-adjusted geometric control chart is presented in this study [12]. The discussion emphasizes how important risk-adjusted control charts are for managing patients' diverse medical conditions and enhancing practice quality assurance. [13] This study offers a thorough review of the use of these charts in monitoring medical processes by grouping them into three primary categories: continuous variables, characteristics, and time-weighted. This novel strategy addresses a crucial component of patient

care by improving healthcare procedures. The application of risk-adjusted proportion non-conforming control charts for health-related variables, such as severe disease in cardiac patients over a 10-month period, is demonstrated by this study ^[14]. This work emphasizes how graphical approaches are underutilized in surgical oncology when tracking unfavorable outcomes, although they are widely used in cardiothoracic surgery and transplantation. It explains popular graphical techniques ^[15]. In order to evaluate the effects of a novel graphical tool on the interpretation of surgeon performance metrics for total knee replacements, this study will take into account patient- and surgeon-specific variables by using risk adjusted control charts ^[16].

For the purpose of to monitor hospital-acquired infections and adverse events in healthcare settings, this article examines the statistical characteristics and design concerns of novel Shewhart-type statistical control charts, or "g" and "h" charts. Compared to traditional binomial-based methods, these charts provide better operational characteristics and sensitivity by utilizing within-limit rules, redefined Bernoulli trials, and probability-based limitations ^[17]. This study shows how control charts can be used to track patient safety results after thyroid surgery. Postoperative adverse effects, including hypocalcaemia and recurrent laryngeal nerve palsy, were prospectively monitored for two years using P-control charts ^[18]. This study ^[19] describes the EWMA control scheme, a nonparametric statistical technique for forecasting and identifying the incidence of breast cancer. This method is completely nonparametric and effective for identifying shifts for multivariate processes because it makes use of rank approaches. The usefulness of control chart methodology ^[20] more especially, P and U charts—in infection control in the healthcare sector is assessed in this study. Risk-adjusted control charts performed better than unadjusted charts; this suggests that risk-adjusted control charts, especially the XmR chart based on the Standardized Infection Ratio, could be useful instruments for infection control in epidemiology. The study ^[21] compares four techniques for determining the incidence rate of congenital malformation: Sets, two versions of Sets, and the Bernoulli CUSUM approach. The potential

for even earlier epidemic identification was demonstrated using modified SPC charts. These results ^[22] highlight the viability and promise of real-time SPC surveillance in improving patient safety through early detection of SSI outbreaks, indicating the need for additional refinement of SPC chart selection and guidelines for outbreak detection. The potential ^[23] for even earlier epidemic identification was demonstrated using modified SPC charts. These results highlight the viability and promise of real-time SPC surveillance in improving patient safety through early detection of SSI outbreaks, indicating the need for additional refinement of SPC chart selection and guidelines for outbreak detection. The experiment ^[24] explored geometric-based SPC chart design approaches like g and h charts for tracking nosocomial infections and side effects. The charts improved operational features and sensitivity by incorporating within-limit rules, in-control rules, Bernoulli trials, and probability-based limitations, enhancing detection power. This study ^[25] presents AM-ADS, a unique Appliance Monitoring and Anomaly Detection System that uses power profiles to identify anomalies in household appliances. In order to maximize detection accuracy, AM-ADS uses an Artificial Neural Network (ANN) based method for sufficient historical data and a Control Chart (CC) based method for insufficient historical data. This study ^[26] examines the use of control charts and statistical process control (SPC) in the healthcare industry, following the field's development from industrial manufacturing to patient care.

Unidentified out-of-control occurrences were found by the use of one-sided control charts, both univariate and multivariate, which improved medical decision-making in patient care. The study highlights the importance of control charts in giving a thorough picture of a patient's development over time, despite its retrospective character ^[27]. This information can help medical professionals manage patients with chronic respiratory problems. The importance of run charts ^[28] as an analytical tool for healthcare quality improvement initiatives is emphasized in this research. Healthcare workers can objectively evaluate process and system changes over time with the help of this helpful method, which gives a consistent approach to construction, use, and interpretation. The SPC

technique^[29] makes it possible to track a consistent improvement in the amount of time needed to administer corticosteroids as well as identify variations with specific causes. Corticosteroid administration time, admission rates, and post-corticosteroid emesis are all significantly reduced when a standardized strategy for corticosteroid therapy is used. This article^[30] describes the use of statistical quality control charts, which date back to Dr. Walter Shewhart's research in 1924, for process analysis and improvement in the healthcare industry. This study^[31] presents a new fuzzy control chart method for process monitoring and shows through a power test and real-world example how effective it is over the conventional Shewhart X bar chart. It also shows increased sensitivity to small changes and improves the identification of desirable shifts without adding complexity to the chart. This work^[32] presents a new method for creating fuzzy control charts that may be used to different processes. It is based on Shewhart control charts and fuzzy theory. The suggested method performs better at quickly identifying process alterations, suggesting that it has broad potential for use in pulmonary department. Unusual patterns^[33] were investigated in a fuzzy setting, and an industrial example's outcomes confirmed the model's heightened sensitivity and conformity to real-world scenarios in comparison to traditional methods—especially for trapezoidal fuzzy numbers. For the purpose of monitoring processes with numerous categories^[34] this paper presents an extension of the standard p-chart, known as the fuzzy multinomial chart (FM-chart). FM-charts perform better than conventional p-charts because they incorporate degrees of membership from the multinomial distribution. This study^[35] assesses the control chart according to average run length using triangular fuzzy numbers and simulation studies. The outcome highlights the efficacy of the fuzzy multinomial control chart by demonstrating its sensitivity and average run lengths reducing when the process is out of control. The paper^[36] addresses outlier sensitivity by proposing robust estimators for process parameters in g-type quality control charts. Two novel estimators are produced by truncating distributions and taking advantage of the geometric

distribution's memory less characteristic. A pilot project^[37] that used u-charts to track average daily cases of communicable, environmental, and social diseases involved 553 sentinel general practitioners (GPs) throughout France. Based on baseline incidences, control limits were established, and if averages deviated from these limits, alarms were sent out. This study^[38] examines the corona virus epidemic globally, focusing on pre-growth and post-growth phases. The EWMA and attribute c chart provide valuable insights for doctors to understand the situation and take necessary precautions.

The length of stay (LOS)^[39] for diabetic inpatients in two national healthcare systems is being tracked by this study using SPC techniques, more especially I-MR charts. The insights obtained from examining the I-MR charts can be used by decision-makers and healthcare professionals to resolve variances in LOS and improve patient outcomes. For real-time monitoring,^[40] GLM-based CUSUM and EWMA control charts are suggested; these provide better detection capability than current techniques. To ensure desired performance^[41], a bootstrap technique is incorporated into the proposed control chart to identify control limits. The efficacy of the suggested method is demonstrated by simulation studies and actual data analysis, underscoring its benefits over current nonparametric control charts for count data monitoring. In order^[42] to overcome the shortcomings of traditional approaches in situations involving hazy or unclear data, this work presents a neutrosophic Hotelling-T² control chart. Its efficacy in identifying changes in the process average is demonstrated by simulation-based performance evaluation. The Shewhart control chart's^[43] effectiveness in identifying occupational asthma in workers is examined in this study. This highlights its ability to be used as a preventative measure in occupational health surveillance to control occupational asthma risks. Compared^[44] to the conventional Shewhart approach, the study created a novel control chart with modified upper and lower limits for the present batch by utilizing the empirical Bayesian method. Findings showed that, in comparison to the Levey–Jennings control chart, the empirical Bayesian approach provided more sensitivity and earlier deviation detection, improving daily control in CBC laboratory tests and

possibly benefiting patient care. The effectiveness of two control charts, ^[45] individual/moving range (XmR) and Tukey (TCC), in analyzing a single observation over a given time period is compared in this research. Practitioners looking to maximize control chart selection for effective quality monitoring may find this study to be rather insightful. The work presents ^[46] a high-accuracy magnetic resonance imaging approach for the diagnosis of cancer tumors' and metastases that supports medical interpretation. It makes use of a multivariate Hotelling's T^2 control chart, discrete wavelet transform feature extraction, and genetic algorithm dimension reduction. This strategy offers encouraging results for both patients and healthcare professionals, addressing the urgent demand for accurate, non-invasive diagnostic tools in the treatment of cancer. The paper focuses on monitoring patients with hypertension's diastolic blood pressure (DBP) by using SPC techniques; particularly \bar{X} & R charts ^[47]. This method emphasizes how crucial ongoing observation is to the efficient treatment of long-term conditions like hypertension. The study ^[48] assessed how well the CUSUM control chart methodology identified overly high acquisition rates of antimicrobial-resistant (AMR) microorganisms. Overall, the incidence rates were steady, and both hospitals' CUSUM alarms were activated. According to the study, CUSUM technique can be a useful tool for monitoring antimicrobial resistance (AMR) in healthcare settings and be used in conjunction with current infection control efforts. According to the table the most of the articles are from fuzzy control charts. When other requirements are met, we would like to employ the theoretical model in a competitive setting to create control charts. There is growth in control chart many techniques are combined with control to get adequate results. Some of the papers were about process capability: An effective statistical instrument for evaluating a process's effectiveness and the ability in statistical process control (SPC) is the Process Capability Index (Cpk) ^[49]. Time series control charts: Statistical modeling involves time-series effect fitting, and residuals from these fits are subjected to typical control-chart procedures. To display estimates of the systematic effects, the fitted values can be shown independently ^[50], etc.

Based on the author or authors and the control chart that was employed in the study, researchers can quickly assess the content of papers. Researchers can concentrate on their area of interest and avoid returning to work. Over the past three decades, the control charts have shown themselves to be excellent tools for raising the standard of the healthcare sectors.

4.7 Limitations

The set of instructions relates to the control chart's assumptions fulfilment, namely the availability of enough data to ensure an accurate approximation of the data distribution, the stationary feature of the data, the data independence, and the chart parameters. Infractions of each assumption will lead to the development of a baseline model for monitoring purposes, the adoption of a model that accounts for a lack of data or regular updates to the chart parameter, corrections to the standard deviation calculation, data transformation, or the creation of a distribution-specific control chart. Furthermore, throughout the control chart building phase, application convenience should be taken into account. Some of the monitoring process's challenges can be solved by modifying an existing monitoring instrument from the healthcare industry or by utilizing an intuitive monitoring variable.

5. Conclusion

This study demonstrates how important statistical process control (SPC) charts are for improving healthcare quality in different countries and departments. Through a focus on 50 relevant publications selected from an initial collection of 300, the study illustrates how control charts have become increasingly popular and important in healthcare since 2015. Although the United States is the leader in using these charts, other nations are starting to realize their potential as well, including China, India, and Russia, according to the report. P-charts, fuzzy charts, and CUSUM charts are among the most commonly used charts in the departments of surgery, emergency, pulmonary, monitoring, and epidemiology. The study recognizes the difficulties caused by the intricacy of multivariate charts and emphasizes the significance of choosing relevant variables. The possibility for wider application is apparent, particularly in fields such as surgery,

pulmonary monitoring, and epidemiology, even though there lack of researches that directly addresses departmental healthcare. The study highlights that prospective investigations are more effective than retrospective analysis at providing insights into standard procedures. This comprehensive review fills a major gap in the literature by offering a complete examination of SPC chart applications in healthcare, utilizing various visualizations and statistical tools. It establishes a basis for subsequent investigations to go deeper into particular chart techniques, attributes, and situations. To improve the comprehension and application of control charts in the healthcare sector, larger-scale research is advised in order to generalize findings. By doing so, this research contributes valuable insights that can guide healthcare professionals and researchers in effectively utilizing SPC charts to improve patient outcomes and overall healthcare quality.

6. Declarations

- Funding: This research does not receive any external funding.
- Conflict of interest/Competing interests: Author A declares that he has no conflict of interest. Author B declares that she has no conflict of interest.

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