

RUN AND CONTROL CHARTS IN A NUTSHELL

WHAT IS A RUN VERSUS A CONTROL CHART?

Run charts and *control charts* are both ways to display data (Y axis) over time (X axis). Both charts can help you to differentiate types of variation in your data. **Common cause variation** is the variation that is inherent in every process and is due to chance. It can mean that several people contribute to a process as a matter of routine, and thus some variation, some randomness would be expected. *Common cause variation* is neither desirable nor undesirable. **Special cause variation** is the variation in a process that can be assigned to identifiable events, that is, some event has occurred to which the variation can be attributed, it is not a random occurrence. These events may or may not under your control. For example, a change in a process might increase the number of patients screened; bad weather may increase the number of no-shows. Either way, special cause variation is different.

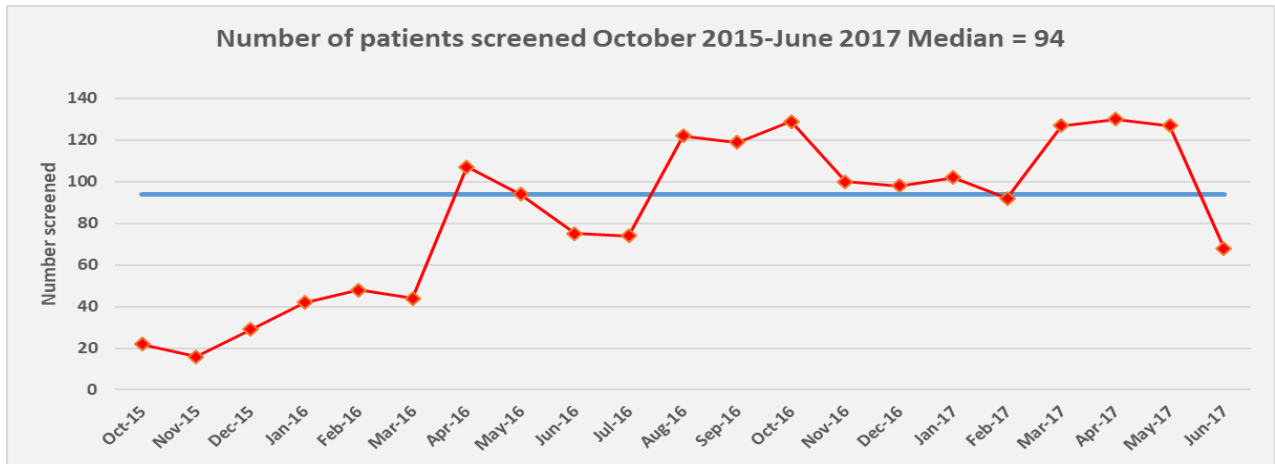
The difference between a run chart and a control chart is what reference points they use to identify variation. A run chart is the simplest: it uses the **median** as the central line reference point. The median is the central point in a count of events. A control chart is more complex: it uses the **mean** (average) as the central line of reference. Because it uses a mean, it can also display standard deviations from the mean. There are several kinds of control charts depending on the type of data that is displayed.

Let's look at some screening data. *# screened* is the number of patients whose screening has been documented in the EMR. *# visits* is the number of patients who were eligible for screening who were seen in the clinic that month, that is, the number of *opportunities* for screening to occur.

Month	# screened	# visits	Month	# screened	# visits
Oct-15	22	51	Jan-17	102	113
Nov-15	16	28	Feb-17	92	101
Dec-15	29	29	Mar-17	127	136
Jan-16	42	98	Apr-17	130	140
Feb-16	48	93	May-17	127	139
Mar-16	44	97	Jun-17	68	73
Apr-16	107	118			
May-16	94	97			
Jun-16	75	83			
Jul-16	74	77		Mean =	84
Aug-16	122	132		Median =	94
Sep-16	119	129			
Oct-16	129	144			
Nov-16	100	119			
Dec-16	98	122			

INTERPRETATION OF A RUN CHART

Here is the data from the table above in a run chart. It is a count of the number screened.



Key terms

Run: A “run” is one or more consecutive points on the same side of the median.

Based on the runs, you are looking for something that is not random: shifts, trends, too much or too little variability. Data points on the median do not count.

Shift: A run that is too long (6 or more consecutive points on one side of the median).

Trend: A run with consecutive increases or decreases in data (5 or more consecutive points).

Too much or too little variability: Too few or too many runs (depends on number of data points).

Shifts and trends are statistically significant.

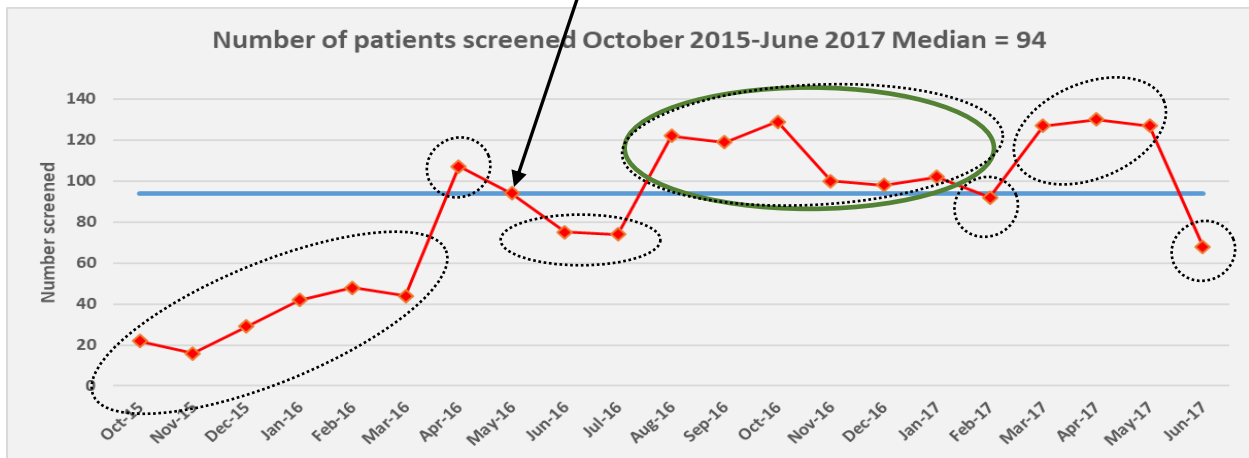
How many data points do you need? The table below provides some guidance.

Number of observations excluding points on the median	Lower limit for the number of runs	Upper limit for the number of runs
13	4	11
14	4	12
15	5	12
16	5	13
17	5	13
18	6	14
19	6	15
20	6	16
21	7	16
22	7	17
23	7	17
24	8	18
25	8	18
26	9	19
27	10	19
28	10	20
29	10	20
30	11	21
31	11	22

13 data points are the absolute minimum number that you need to interpret a run chart, with no fewer than 4 runs and no more than 11 runs among those 13 data points.

How to interpret the run chart based on our data:

It appears there are 21 data points, but May 2016 is on the median, so there are 20 data points.



There are 7 runs (dotted lines) (6 is the lowest number allowed for 20 points), one of those runs is also a **shift (solid green circle)**, no trends.

Interpretation: Something different happened between August 2016 and January 2017 to increase the number screened. What? Final interpretation is always in context: what was happening that was different that contributed to special cause? Was it something YOU did? You sure? Statistically significant and significant in terms of your program or services are two different things.

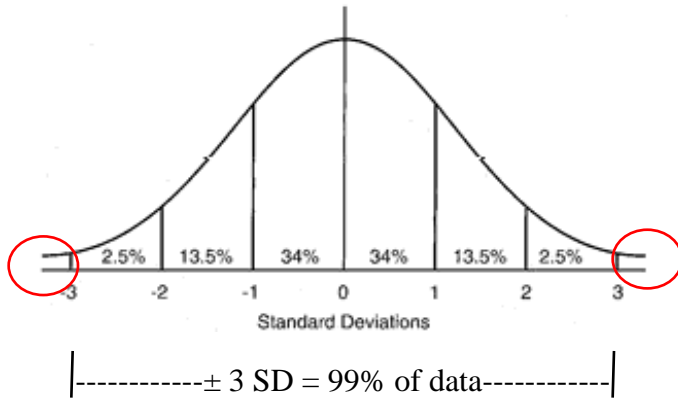
Important take away: Interpretation of *common cause variation* and *special cause variation* is 100% context dependent. They are neither desirable nor undesirable by themselves. Sometimes “business as usual” is effective enough; sometimes it is not. Sometimes a special cause signifies you are going in the right direction, and sometimes it signifies you are going in the wrong direction. If you don’t understand the context of your practice, you cannot interpret a run chart.

INTERPRETATION OF A CONTROL CHART

Because a control chart uses the **mean** as the central reference point, the standard deviations from the mean can be calculated. Three standard deviations above the mean refers to the **Upper Control Limit (UCL)** and three standard deviations below the mean refers to the **Lower Control Limit (LCL)** of the data. In some control charts the lower limit is always “0”.

Three standard deviations above and three standard deviations below the mean account for about 99% of data under a bell curve. This 99% is considered **common cause variation** (the chance randomness that occurs with business as usual). Because **Sigma Σ** (upper case) is the symbol used for

standard deviation, the term six sigma refers to three plus three standard deviations beyond the mean, that is, 99% of the data. The other 1% of data represents **special cause variation (red circles)**, something that is different, that is deliberate, nonrandom chance from “business as usual.”



Community Health Center, Inc.'s **CLINICAL WORKFORCE DEVELOPMENT** NATIONAL COOPERATIVE AGREEMENT — A Program of the Weitzman Institute

**How it works:
The Bell Curve and Control Chart**

Y axis is the data values.

X axis is points in time: days, weeks, quarters

- Control chart uses a Mean.
- A “signal” is 3 standard deviations (3SD) above (+) or below (-) the Mean.
- Only 1% of data points should occur at $\pm 3SD$.
- So a signal is significant at $p < .01$.
- That is, a signal is not a random event.
- Whether a signal is “good” or “bad” is in the interpretation.

Visit: www.chc1.com/nca | Contact: nca@chc1.com

When you read a control chart, you are looking for anything outside of the 99%, that is, for that 1% of **special cause variation**. These are called **signals**, sometimes called special causes, and are statistically significant. The control chart cannot explain to you why a special cause occurs or if it is desirable or undesirable, nor can it distinguish between statistical significance and clinical significance in your practice. That is 100% your interpretation. A signal just asks you to pay attention.

Types of Signals:

Trends: 7 or more data points in a row that increase or decrease (or 6 in a row if there are fewer than 21 data points; two successive points of the same value count as one).

Shifts/runs: 8 or more data points in a row that fall either above or below the center line/mean.

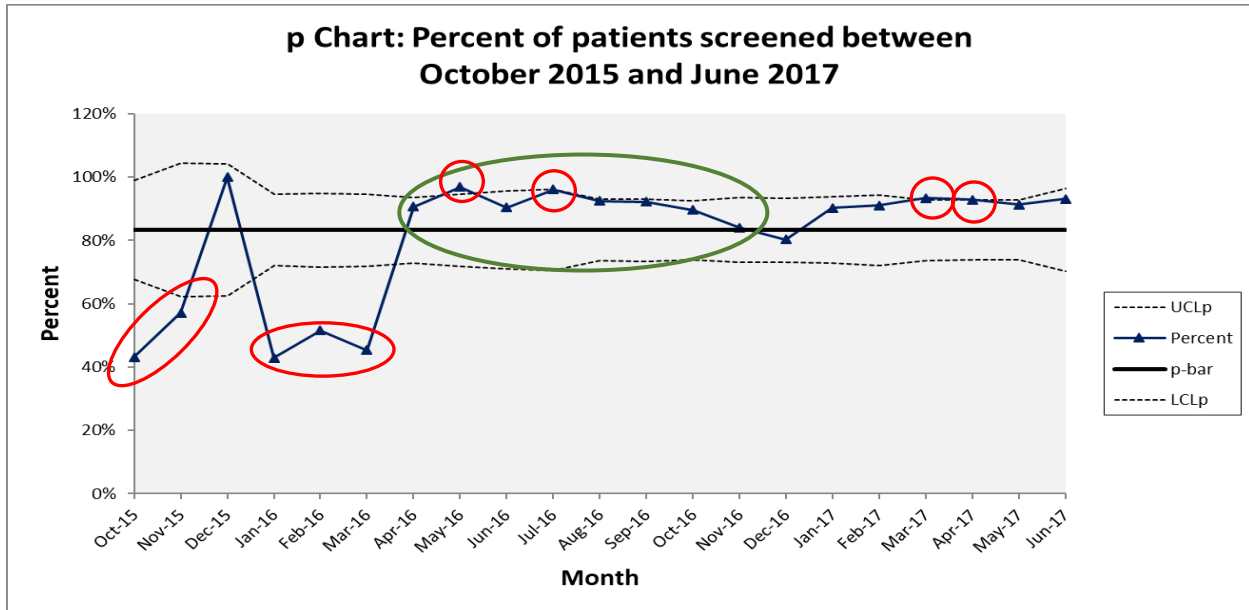
Special cause: any single data point that is above the **Upper Control Limit (UCL)** or below the **Lower Control Limit (LCL)**.

We put the data in the original table into a **control chart template**, specifically a **p chart**. The numerator is the # screened and the denominator is the # visits for each month. Here is the output:

Date	Numerator	Denominator	Sigma	Individual Percent	LCLp	\bar{p}	UCLp
Oct-15	22	51	0.052235	0.431373	0.676236	0.83294	0.989644
Nov-15	16	28	0.070496	0.571429	0.621452	0.83294	1.044428
Dec-15	29	29	0.06927	1	0.625131	0.83294	1.04075
Jan-16	42	98	0.037682	0.428571	0.719895	0.83294	0.945985
Feb-16	48	93	0.038681	0.516129	0.716896	0.83294	0.948984
Mar-16	44	97	0.037875	0.453608	0.719314	0.83294	0.946566
Apr-16	107	118	0.03434	0.90678	0.72992	0.83294	0.93596
May-16	94	97	0.037875	0.969072	0.719314	0.83294	0.946566
Jun-16	75	83	0.040945	0.903614	0.710104	0.83294	0.955776
Jul-16	74	77	0.042511	0.961039	0.705408	0.83294	0.960472
Aug-16	122	132	0.032468	0.924242	0.735536	0.83294	0.930344
Sep-16	119	129	0.032843	0.922481	0.73441	0.83294	0.93147
Oct-16	129	144	0.031086	0.895833	0.739683	0.83294	0.926197
Nov-16	100	119	0.034196	0.840336	0.730353	0.83294	0.935527
Dec-16	98	122	0.033772	0.803279	0.731623	0.83294	0.934258
Jan-17	102	113	0.035092	0.902655	0.727665	0.83294	0.938215
Feb-17	92	101	0.037118	0.910891	0.721587	0.83294	0.944293
Mar-17	127	136	0.031987	0.933824	0.736979	0.83294	0.928901
Apr-17	130	140	0.031527	0.928571	0.73836	0.83294	0.92752
May-17	127	139	0.03164	0.913669	0.73802	0.83294	0.92786
Jun-17	68	73	0.04366	0.931507	0.701961	0.83294	0.963919

The **p bar is the mean percentage**, which is 0.83294, or 83%. Because the denominator (# visits) changes, the individual percent is recalculated each month, as are the ± 3 standard deviations (UCL and LCL). That is, they **vary**.

The control chart below is a p chart, that is, proportion or percentage. Each data point represents the **percentage** of patients screened between October 2015 and June 2017. While you can often eyeball where a data point sits relative to the **p-bar** or **UCL** and **LCL**, sometimes you need to look at the output data, as in the table above. None of the data points are on the mean (November has a value of 0.840, not 0.832). July is slightly above the UCL (0.961 v 0.960), as are March (0.933 v 0.928) and April (0.928 v 0.927).



There is a shift of 8 data points above the mean between April and November 2016 (solid green circle). There are four signals above the UCL, two of which occur within that shift (May and July 2016 red circles), and two of which occur in what is almost shift (March and April 2017 red circles). There are also some data points below the LCL in the first few months of data gathering.

Interpretation: The shift above the mean beginning in April 2016 suggests that after some false starts in the earlier months, the new screening process began to consistently capture more patients, that is, it improved in a desired direction. Following a bit of a dip in December 2016, it seemed to improve again: if we had data for July and August 2017, we might see this effort sustained—or not.

How does this compare to the run chart of the same data? The run chart indicated a shift between August 2016 and January 2017 to increase the # screened; the dip in December 2016 did not show up. The control chart suggests the shift may have started as early as April 2016 but didn't last as long as the run chart indicates. Either way, a change in the screening process has begun to result in improvements in capturing the number of eligible patients who get screened.

Important take away: Interpretation of *common cause variation* and *special cause variation* is 100% context dependent. They are neither desirable nor undesirable by themselves. Sometimes “business as usual” is effective enough; sometimes it is not. Sometimes a special cause signifies you are going in the right direction, and sometimes it signifies you are going in the wrong direction. If you don’t understand the context of your practice, you cannot interpret a control chart.

TYPES OF DATA

The example used above used discrete counts of # screened and # visits (*opportunities* to screen). There are two types of data in control charts, and the type of data and size of the sample determine which control chart to use. There is only one type of run chart, but there are many different types of control charts. Sometimes, more than one type of chart can be used, depending on your question.

1. Attribute data: count
2. Variables data: measure

Attributes data: counting discrete events as whole numbers

Attributes data sometimes also are referred to as discrete data. These types of data represent *counts* of occurrences/events/things that can be categorized, and that either happened or did not happen, that fit the category or do not fit the category, e.g., screened/not screened. Attributes data is counted in whole numbers, e.g, you can have 1 screening, 2 screenings, or no screenings but not 1.5 screenings.

Attributes data can also be expressed as a rate or percentage. Attributes data is a count of events ($\# \text{screened} / \text{numerator}$) against how many *opportunities* exist for those events to occur ($\# \text{visits} / \text{denominator}$). Most often, control charts are used to find **errors**, that is, something that is undesirable, such as infections among hospitalized patients. A control chart assumes that errors are rare events, that is, they take place outside of 99% of the data.

You have to decide *what* you are counting: screened/not screened; depressed/not depressed; referred/not referred; infected/not infected. What is your numerator? What is your denominator?

There are four control charts that can be used for attributes data:

- C chart
- U chart
- P chart
- NP chart

Variables data: measuring values

Variables data generally represent *measurements* on a continuous scale that could have an infinite number of possible values. Examples include the time to complete a process, systolic blood pressure measurements, patient satisfaction scores, and length of stay. Unlike attributes data, variables data does not count errors. Variables data do not have to be in whole numbers, e.g., you can have 25.5 minutes.

There are three control charts that can be used for variables data:

- XmR chart
- X & R chart
- X & S chart

ATTRIBUTES DATA: HOW TO DECIDE WHICH CHART TO USE

Key question: Can the event being counted happen more than once in a time period to an item?

That is, there are multiple opportunities for something to go wrong.

If the answer is "yes," the event can happen more than once (multiple opportunities), then you are counting the number of *defects or number of non-conformances*.

- Examples include: number/rate of patient falls in a month (a patient can fall more than once in a month); number of documentation errors during an encounter (there can be more than one error during an encounter, such as not documenting in multiple required fields).
- Counting defects calls for the use of a C chart or U chart.

If the answer is "no," the event can happen only once, you are counting *defectives or non-conforming units*.

- Examples include deaths, C-sections for a patient during an admission, one no-show appointment for a patient on a day, a wound infection arising from a single procedure.
- If you are comparing an item to a standard and then classifying it as whether it meets the standard or not, then you are also counting *defectives or non-conforming units*. Examples include whether or not screening occurred or immunizations were given.
- Counting defectives calls for the use of a *P chart or NP chart*.

Which chart to use for attributes data?			
Can the error event happen more than once?			
Yes: the event can happen more than once Counting the number of <i>defects</i> or number of non-conformances Count of defects = numerator		No: the event can happen only once Counting number of <i>defectives</i> or non-conforming units	
Are the sample sizes (denominator) equal? That is, does each data point have the same denominator? Yes C Chart	Numerator: count of defects	Are the sample sizes (denominator) equal? That is, does each data point have the same denominator? Yes NP Chart	Numerator: count of defectives
	Denominator: a stable number that does not vary more than 20%, e.g., number of employees		Denominator: a fixed number set in advance, e.g., per 100 opportunities
	Ex: count of staff finger sticks per month		Ex: audit 100 charts to determine if colon screening was documented
Do the sample sizes (denominator) vary? That is, does each data point have a different denominator? Yes U Chart	Numerator: count of defects	Do the sample sizes (denominator) vary? That is, does each data point have a different denominator? Yes P Chart	Numerator: count of defectives
	Denominator: total number of opportunities for defect to occur		Denominator: sample size, number of opportunities for defect to occur
	Ex: fall rate is measured by number of falls (numerator = defects for X period of time) against number of opportunities for falls (denominator = patient census for X period of time, which can change)		Ex: Percent of patients in panel X with A1c>9 in first quarter of 2018

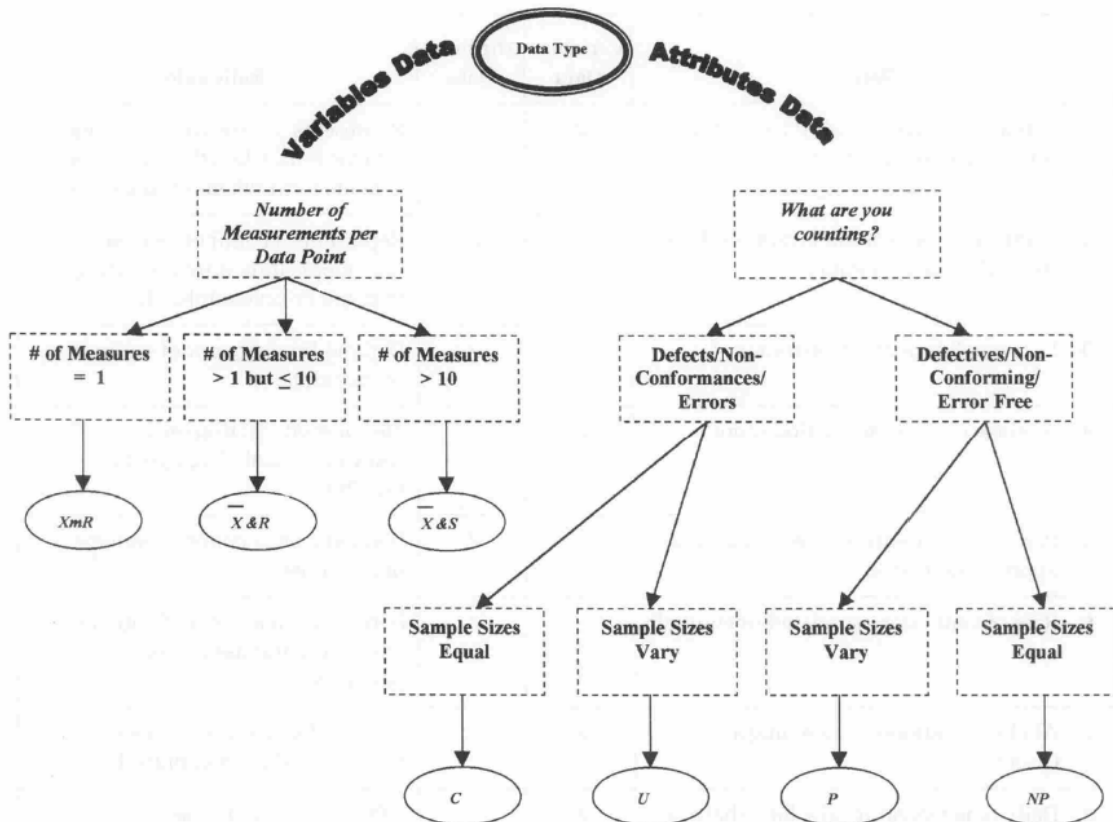
VARIABLES DATA: HOW TO DECIDE WHICH CHART TO USE

Key question: What is the size of the sample for each data point?

Which chart to use for variables data?		
What is the size of the sample for each data point?		
Sample size	Chart to use	
One data point = one value	XmR	Charts the difference between successive points when you are looking for how much something varies from one data point to the next, such as monthly budget

<p>One data point = a set of 2-10 subvalues where each data point represents the same number of subvalues, e.g., each data point is the average of 6 subvalues</p>	<p>X-Bar and R</p>	<p>Sample five cycle times a day for 10 days: each of the 10 data points represents the average of the five cycle times for that day</p>
<p>One data point \geq a set of 11 or more subvalues where each data point represents the same number of subvalues, e.g., the average of 20 data values</p>	<p>X-Bar and S</p>	<p>Patient satisfaction scores are measured on a continuous scale from 1-5. Chart 18 months of satisfaction scores, where each of the 18 data points represents the average of 20 individual scores</p>

Control Chart Selection Process



Reference: Amin, S.G. (2001) Control Charts 101: A Guide to Health Care Applications. *Quality Management in Health Care*, 9(3), 1-27.

Important take away: If you don't understand the type of data you have, and how it is being defined, if you don't have a clear aim or question about your data, you cannot develop a control chart. As with run charts, interpretation of *common cause variation* and *special cause variation* is 100% context dependent. They are neither desirable nor undesirable by themselves. Sometimes "business as usual" is effective enough; sometimes it is not. Sometimes a special cause signifies you are going in the right direction, and sometimes it signifies you are going in the wrong direction. If you don't understand the context of your practice, you cannot interpret a control chart.

Other references:

Nelson, E. C., Splaine, M. E., Plume, S. K., & Batalden, P. (2004). Good measurement for good improvement work. *Quality Management in Healthcare*, 13(1), 1-16.

Perla, R. J., Provost, L. P., & Murray, S. K. (2011). The run chart: a simple analytical tool for learning from variation in healthcare processes. *BMJ Quality & Safety*, 20(1), 46-51.

Provost, L. P., & Murray, S. (2011). The health care data guide: learning from data for improvement. *John Wiley & Sons*.