LEADING STRATEGIES

The Death of Hunch-Based Decision Making in SEM

By Morgan Blair and Alex Zanidean

Data interpretation can be difficult. Data visualization techniques from the manufacturing industry make interpretation easier. Control charts display trends in context, so it is clear when performance is truly changing and when it is not. Decision makers know when to act, when to maintain, and when to celebrate. This article discusses the use of control charts to monitor performance in SEM.

Fiscal constraints, accreditation requirements, accountability frameworks, and increasing competition in the market have led to greater emphasis on the importance of data-informed decision making to maintain institutional relevance. Data-informed decision making, evidence-based decision making, and data-driven decision making are all buzz phrases used to describe the act of considering data and/or trends, as opposed to a hunch, while making a decision. This article uses the term "data informed" to refer to this concept, yet it is important to recognize that more goes into decision making than data alone.

Data-informed decision making has received considerable attention in strategic enrollment management (SEM) (Black 2010; Bontrager, Ingersoll and Ingersoll 2012; Langston, Wyant and Scheid 2016; Pirius 2014) and higher education literature (Booth 2013; Cervetti, Royne and Shaffer 2012; Marks and O'Connell 2003; McClintock and Snider 2008; Shen and Cooley 2008; Vorlotta 2012; Westdijk, Koliba and Hamshaw 2010; Wood, Bethune, Preston and Cleaver 2016).

The premise that the environmental constraints that threaten institutional relevance can be outsmarted by using data to inform strategic decisions is intuitively attractive. Institutions that employ data to inform decisions regarding SEM practices may become increasingly agile and responsive to market conditions (McClintock and Snider 2008). The need to be agile and flexible in today's market is underscored by pressures to manage costs while growing revenue streams (Black 2010). Black (2010) states that institutions that utilize SEM data properly will capitalize on external opportunities while moderating threats and align enrollment strategies with institutional goals. He posits that the greatest threat to institutions is that they ignore trends that shift slowly. For example, upward trends in enrollment may lull institutions into a false sense of security, which can cause leaders to overlook the causes underlying enrollment trends.

Student demographics, trends, and external pressures are constantly in flux. Therefore, the entirety of a situation (*e.g.*, the changing nature of student demographics) may only become evident as the planning process unfolds (Chance 2010). Risk management, combined with planning, may help mediate uncertainties and reduce an institution's vulnerability in a changing market (Achampong 2010). For example, SEM practices can be used to minimize costs while growing revenue, providing institutions with maximum agility (Black 2010). In managing risk, Achampong (2010) recommends that institutions systematically identify and evaluate risks, assess strategies for action, and continuously monitor the strategies that are implemented. This exemplifies data-informed decision making for the purpose of continuous improvement.

Unfortunately, it is not that simple. Even for institutions that are data rich, interpretation of data to make informed decisions can be difficult. Data interpretation can be intimidating; the impact of one's actions weigh on the decision maker when facing multiple graphs and often conflicting information. Further, considering the ways in which data are typically displayed, it is no wonder that people often struggle with interpretation. Typical graphs and reports require decision makers to spend time and energy focusing on meaningless fluctuations in data, muddling their way through month-to-month comparisons, or, worse, trying to interpret data from a single point in time. None of these efforts truly informs a decision, and this may cause even the most savvy decision maker to disregard the data and rely instead on an occasional hunch.

Yet data interpretation does not have to be difficult. A simple lesson from manufacturing can move an institution along the path toward simplified data interpretation, and this can change the way in which decision makers interact with and use data.

Control charts, although frequently used in the manufacturing industry, are relatively new to higher education. Control charts extract the signal from the noise. They clearly display historical trends in context so the user can identify when performance is truly changing and when it is not. By identifying a few simple patterns in the data, decision makers know when to act, when to maintain performance, and when to celebrate. By reenergizing an old performance measurement process with new techniques and applying it to a different field, we can change the way we think about and use data to inform decision making. We can increase our institutions' focus on data-informed refinement of performance for continuous improvement.

This article explores how to use control charts to make data interpretation easy and to thereby promote data-informed decision making. This approach can be applied to SEM and beyond. After reviewing the basics of control charts, this article outlines three easy patterns to watch for and demonstrates how control charts help to monitor and refine performance for continuous improvement.

The Basics of Control Charts

Who's heard of control charts?

Control charts have been around for nearly a century. Shewhart (1986) developed control charts in his work to improve the reliability of Bell Telephone's transmission systems in the early twentieth century. Control charts are essentially a way of graphing data within the context of how a given metric has performed in the past and include parameters that allow one to identify when changes in performance are statistically significant. Control charts provide a visual sense of what is normal and what is not, without the need to peruse long data tables or understand advanced statistics. In fact, one does not need a working knowledge of statistics to accurately interpret a control chart. One needs only to be able to recognize simple patterns.

Today, control charts are used in Six Sigma (Breyfogle 2003) to monitor process stability and control and as an analysis tool for process improvement. This approach is often used in the manufacturing industry, where the production of widgets is monitored for exactness. Inputs (raw materials) need to be of consistent quality, and the environment (facility conditions, process) needs to be held constant or improved to achieve ever-increasing standards of efficiency. Control charts

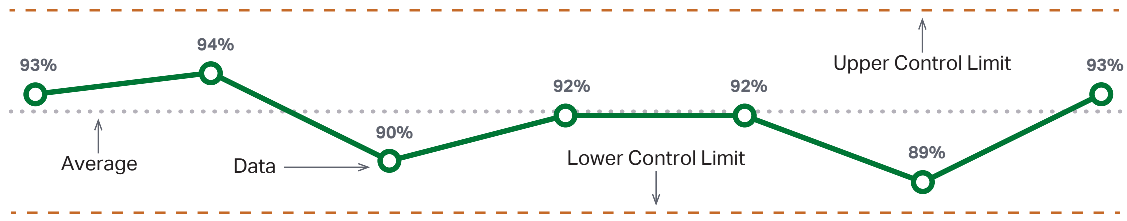

FIGURE 1 ➤ The Elements of a Control Chart

can be useful in other industries as well. Higher education is a prime example.

As control charts are applied to other industries, there may be some nuanced changes to the purpose of their use. After all, educating students is not the same as producing widgets in a controlled facility. Rather, higher education deals with much more complex inputs (students who arrive with their own backgrounds, abilities, expectations, and needs) and multifaceted environments (insert any person-based higher education process). Thus, in higher education, control charts could be used primarily to monitor and refine performance for continuous improvement.

Surprisingly, control charts are relatively new to higher education. Apart from one paragraph in the *Handbook of Institutional Research* (Howard, McLaughlin and Knight 2012), a review of the literature turned up only three articles on the use of control charts in higher education. There, they have been used primarily to assess teaching and/or learning (Cervetii, Royne and Shaffer 2012; Marks and O'Connell 2003; Walshe 2008). No articles were identified on the use of control charts for assessing institutional-level performance. Given the demand for data-informed decision making in higher education, the absence of publications on the use of control charts as a means of informing decisions to improve performance is astonishing.

What is a control chart, and how is it used?

Control charts clearly display data within the context of historical trends so the user can identify at a glance when performance is truly changing and when it is not. The user must recognize a few simple patterns. A large part of human intelligence is based on our ability to recognize patterns (Mattson 2014; Zakharov, Voronin, Ismatullina and Malykh 2016). Pattern recognition is innate; it helps us survive by helping us meet basic needs, like finding food, recognizing safe versus unsafe situations, and finding mates. It also helps us interpret data and is key in decision making (Jain, Duin and Mao 2000). Once decision makers understand that data interpretation is about pattern recognition, it becomes easy.

Control charts comprise three essential elements: the performance data, central line (average of performance over time), and upper and lower control limits (*see* Figure 1). The control limits indicate the range within which performance could be expected to fluctuate under current conditions. Each control limit is about three standard deviations from the average; together, the space between the control limits encompasses the area under a bell curve (imagine the bell curve flipped on its side). The space between the control limits represents the range of normal variation in performance based on how a metric has performed in the past. Both the central line and the control limits are calculated based on the first five data points, and this comprises baseline performance. All future performance will be compared to baseline performance. It is the yardstick by which to demonstrate improvement.

For example, if the data displayed in Figure 1 represented student retention, it would be appropriate to say that retention rates fluctuated between 89 percent and 94 percent over time, with an average of 91.5 percent. If the institution in this hypothetical example were to

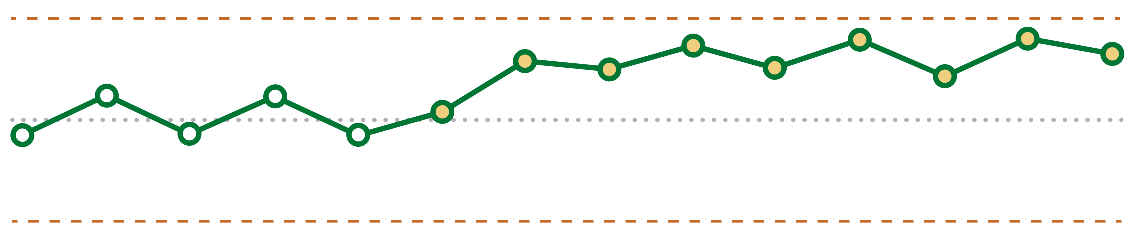

FIGURE 2 ➤ Long Run

maintain all existing programs, supports, and services, retention could be expected to fluctuate between about 86 percent and 96 percent (the approximate value of the control limits). The first five data points—until 2014 in this case—are used to calculate baseline performance; future retention rates are compared to the baseline by watching where they fall in reference to the central line and the control limits. In other words, watch for patterns to occur compared to the baseline.

Three Easy Patterns

Understanding the elements of a control chart allows us to begin to look for patterns in the way the data fall on the chart. Recognizing these patterns in the data makes it easy to know whether to take action to improve performance, maintain current activity, or celebrate. Shewhart (Shewart and Demings 1986) and other authors (Barr 2014; Wheeler and Smith Chambers 1992) developed many patterns, all of which indicate that something of statistical significance is happening in the data. While a description of all of these patterns is beyond the scope of this article, there are three main patterns that appear most often in higher education data: stable performance, long runs, and short runs. Each of these is described separately.

Stable Performance

Stable performance fluctuates slightly on either side of the average but within the control limits. Figure 1 is an example of stable performance. By recognizing when performance is stable, we avoid spending time and energy worrying about normal fluctuations in the data. For example, if performance is stable, we do not need to worry about whether a 3 percent drop in retention between 2014 and 2015 is significant. If performance is stable, we can assume the difference is likely due to random fluctuation and move on. Recognizing stable performance is a time saver, especially for those who have a tendency to explore every little blip in the data regardless of whether the observed change is statistically meaningful.

True Change: Long Runs and Short Runs

True change in performance signals that something has occurred (*e.g.*, a new tactic was implemented) that has consistently caused performance to change. Watch for two performance patterns that signify true change: long runs, and short runs. Long runs refer to eight sequential data points that fall on the same side of the average (*see* Figure 2). Long runs represent subtle change that takes place over the long term, like enrollment that creeps up over the course of a decade. Short runs refer to two out of three data points that fall on the same side of the average but closer to one of the control limits than to the average (Figure 3, on page 45). Short runs represent more extreme change over a shorter duration, like weekly drop-out during a prolonged faculty strike.

Both long runs and short runs indicate that a statistically significant change in performance has occurred. This means that we can be fairly certain that some factor has changed that has consistently altered performance on a given metric. Recognizing true change

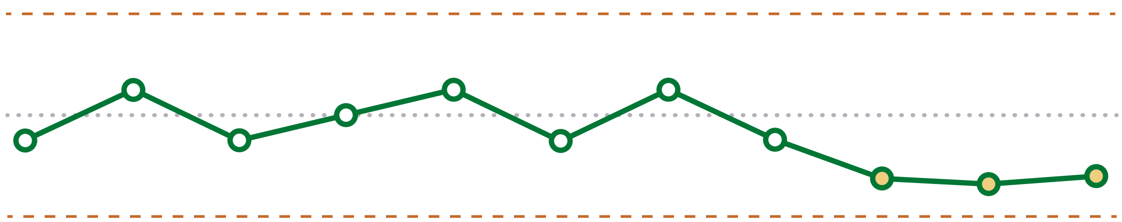

FIGURE 3 ➤ Short Run

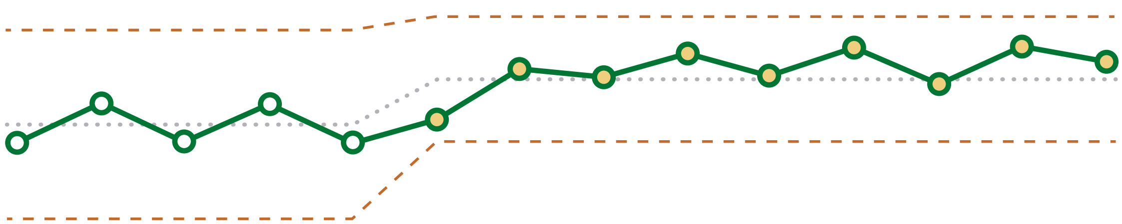

FIGURE 4 ➤ Adjustment to the Control Chart Once True Change Has Occurred

can be particularly useful for providing feedback on whether a tactic had its intended effect on performance. (See additional discussion, below.)

The problem with counting dots to identify patterns is that it is tedious, enahnces the potential for human error, and ultimately does not promote easy data interpretation. To simplify the process, control charts can be designed to give strong visual cues that a pattern is occurring. That visual cue is a jig in the lines that make up the chart: an adjustment to the central line and the control limits to reflect the new status quo once true change has occurred. The central line (average) and control limits (three standard deviations from average) are statistical calculations that provide information about current performance and should be adjusted once a long run or short run has occurred. In other words, a new performance pattern means new parameters for normality. These adjustments can be coded into the design of the control chart using most data visualization software packages.

Figure 4 shows the exact same data as the long run in Figure 2, except the central line and the control limits adjust at the beginning of the long run to provide a visual cue. This visual cue indicates when performance first began to truly change and highlights a pattern. Now all one needs to know is that a jig in the lines means that true change has occurred—no counting dots, no misinterpreting performance patterns. Instead, one can get on with the business of figuring out exactly what caused the change and what to do next.

Recognizing the three patterns equips one to know when to act, maintain, or celebrate. Recognizing when true change is occurring allows for information to be used as feedback on a recently implemented tactic and for tailoring actions that promote continuous improvement. Recognizing stable performance can clarify when

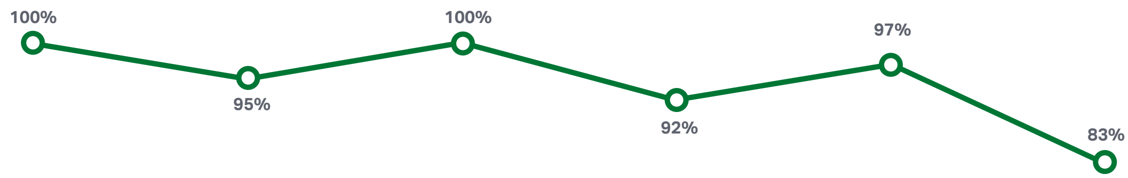

FIGURE 5 ➤ Student Satisfaction Scores in a Typical Line Graph

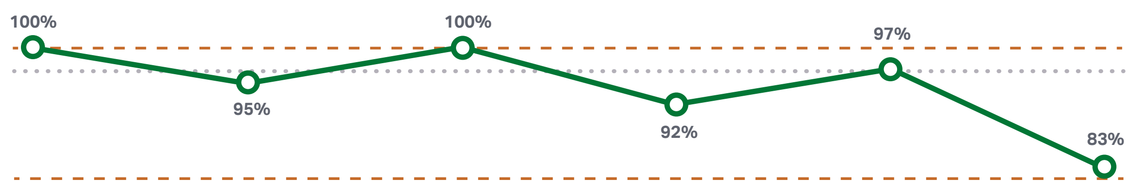

FIGURE 6 ➤ Student Satisfaction Scores in a Control Chart

something has not changed and that any fluctuations are not *that* big of a deal.

These patterns help higher education leaders know when to take action and when to hold tight. For example, a program coordinator was concerned about his program's student satisfaction scores. For years, satisfaction had been between 92 percent and 100 percent, and then it suddenly dropped to 83 percent (*see* Figure 5). The program coordinator was devastated. He was going to have to explain these results to his dean and develop a plan to increase student satisfaction. Viewed in a typical line graph, the results looked concerning: The 14 percent drop looks quite drastic.

When the data were re-graphed using a control chart (*see* Figure 6), a different story emerged. The last data point, which was of so much concern in a line graph, actually fell within the range of normal variation. Therefore, what seemed a drastic drop in satisfaction could be attributed to random fluctuation in the data. It was possible that student satisfaction would be 100 percent the following year. Thus, the program coordinator had nothing to worry about and was able to go golfing rather than write a report.

Monitoring Performance

Control charts can be used to monitor the effect of operational strategy or tactics on institutional performance. By identifying stable performance, long runs, and short runs, one can make decisions about what to do next based on the observed pattern in question. Depending on how performance is tracking relative to the target for a given metric, decision makers can decide to implement additional tactics to improve performance, maintain activity to keep performance stable, or celebrate.

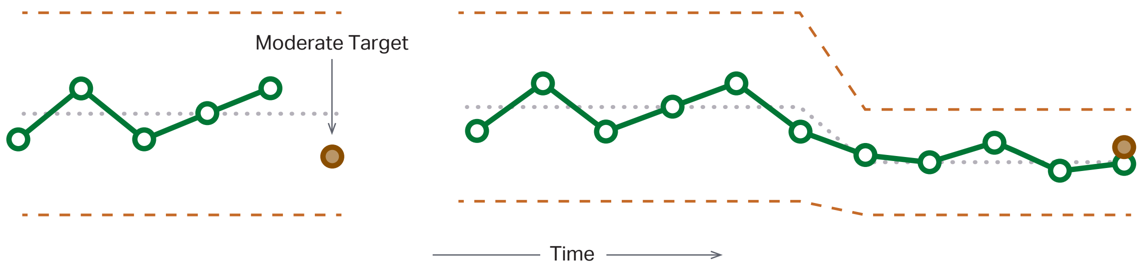

FIGURE 7 ➤ Targets in a Control Chart

Target Setting

Targets for each metric are an important piece of the puzzle when interpreting data and making decisions. After all, without a target, how could anyone know what to strive for? Targets provide decision makers with reference points against which to compare performance; they give an indication of the extent to which performance needs to be improved (if at all) and thereby help decision makers determine which tactics might be implemented to improve performance.

When a target is set on a control chart, it is set for the central line rather than the performance data. In other words, if performance data hit the target next year, we would not consider ourselves to have met the target. The target is not met until the central line is on par with the target (*see* Figure 7). The central line needs to be shifted toward the target. In order to shift the central line, a true change in performance must occur—*i.e.* a long run or a short run going in the same direction as the target.

There is no magic formula for target setting. Usually it's advisable to set targets that require stretching, but not too far. If targets have not yet been set for SEM metrics, then control charts can provide some of the reference information to help set a healthy target. By establishing baseline performance for a metric, average performance can be viewed across time (central line), as can the parameters within which the metric is capable of performing under existing conditions (fluctuation within the control limits). This provides a sense of what is likely to occur.

When setting targets, it is also important to consider the context. It may be desirable to perform at the same level as an external benchmark; or, factors in the environment may impact how aggressive a target might be. The strength of the tactics available to enhance performance on a given metric should also be considered. If several tactics can be implemented and the decision maker is reasonably certain that they will have the intended effect, then a more aggressive target may be desirable. An aggressive target would be close to—or beyond—one of the control limits. If few tactics are available, or if a decision maker is unsure of the tactics' potential impact, it may be preferable to set a moderate target somewhere between the central line and a control limit.

When to Maintain

If the target is set at the current central line, then subsequent tactical decisions are easy. The target has been met, and activity can be maintained. Attention can be dedicated to more pressing metrics where performance is not up to par.

When to Act

When performance falls short of a target, it is time to act. A short or long run going away from the target or stable performance that is consistently below the target is a signal to take action. The appropriate action will depend on the tactics available to improve performance on a given metric. Start with the tactic that is most likely to cause an effect, watch for a pattern to occur, and then layer subsequent tactics for continuous improvement.

When to Celebrate

Celebrate when a short or long run (or series of runs) results in a target being reached, presumably because of the tactics being implemented to improve performance. Reaching a target constitutes an opportunity to congratulate those involved on their hard work, to reinforce ongoing dedication to effective tactics, and to demonstrate to senior leaders how performance has improved. Control charts shine in their ability to demonstrate obvious change in performance relative to a target, even to audiences that have not used control charts.

Layering Tactics for Continuous Improvement

The three patterns can be used as feedback for continuous improvement toward a target. Most decision makers are interested in knowing whether a particular tactic is effective. No one wants to waste time or money on a tactic that does not produce the desired result. Once baseline performance is known, tactics must be layered one at a time in order to observe the effect, starting with the tactic assumed to have the greatest effect. With the implementation of each tactic, watch for a pattern to occur before layering on additional tactics. Using this method, performance can be monitored and continually improved until it is optimal.

For example, consider a personal goal to lose ten pounds. Weighing oneself for five weeks and putting the data into a control chart confirm one's baseline weight and how much one's weight fluctuates from week to week. Two tactics to lose weight include exercise and eliminating sweets from one's diet. Implement only one tactic to begin with, and start exercising for one hour per day. Weigh oneself weekly thereafter and watch for a pattern to occur to determine whether exercising is netting the desired results. After a month, observe a short run: consistently, two pounds are being lost per week. However, after that, weight plateaus, two pounds short of the target. It's time to layer on the second tactic: eliminating sweets. Again, watch for a pattern in the direction of the target weight. This time view the long run: loss of about one-quarter of a pound per week. After eight weeks, the target weight is attained.

Methodical patience in tactic implementation may save time, effort, and money. Decision makers may be tempted to implement several tactics at the same time (a shotgun approach to improving performance), only to be left with the quandary of disentangling the relative effect of each. If multiple tactics are implemented at once, it can be difficult to determine which one actually had the greatest effect on performance. This can result in a commitment to maintaining operationally expensive tactics that may or may not be effective.

Reporting Frequency

There is no optimal reporting frequency for control charts; however, performance is best monitored according to a regular, predetermined schedule. The schedule often depends on a number of factors, including the nature of the variables, *e.g.*, annual enrollment, weekly hits on website), data warehousing and the availability of new data (real-time vs. audited data), the amount of time needed for a tactic to be effective, and stakeholder expectations. Focus on monitoring performance for continuous improvement, reporting frequently enough that true change can be observed within a timeframe that is reasonable and practical for individual circumstances.

Real-World Applications

Like all new things, control charts need to be socialized within the institution in order to be properly adopted. In particular, users need help to understand and build comfort using control charts. As the institutional research department, we were in an optimal position to help users adopt a new approach. When we first started to release reports with control charts, we delivered fifteen-minute workshops to teach users the basics of control charts and gave users opportunities to test their data interpretation skills. For those who could not participate in a workshop, we included a short "how-to" guide along with their reports. As a result, the early adopters have been proponents for further use of control charts, and resistance to their use has been minimal.

In our experience, the use of control charts improved institution-wide data literacy, increased awareness of pertinent issues, and enhanced institutional focus on trends (as opposed to individual data points). With the rules for interpretation being non-negotiable, the conversations about data have been solution focused. For those who frequently compare performance to external benchmarks, a benchmark trend line can be overlaid on a control chart when benchmarks are available. We now use control charts to display data in program review (*e.g.*, specific data related to enrollment, student satisfaction, graduation and retention rates, graduate employment, etc.), performance reporting (*e.g.*, key performance indicators for the board of governors, performance reports on institutional plans, etc.), and ongoing reporting (*e.g.*, survey reports, ad hoc request data, etc.).

Application to SEM

Control charts have the potential to increase data-informed decision making in SEM. They are useful for assessing trends, monitoring performance of key metrics, and evaluating the effect of a tactic on performance. In addition, control charts can be used to demonstrate the impact of SEM on key metrics such as retention when reporting to stakeholders.

Familiarizing the entire SEM committee and the stakeholders who receive SEM reports with the basics of control charts will build comfort with and confidence in SEM. This will increase transparency and enhance a culture of data-informed decision making. Benefits include active participation in data interpretation, stronger engagement in monitoring performance, and a collective focus on continuous improvement.

SEM committees that want to use control charts should consider including members from institutional research and/or information technology. These two areas are particularly well-positioned to work with the software and data necessary to produce control charts.

Limitations

Control charts can be produced using most statistical/data visualization software packages, including Excel®, Tableau®, and R. The producer should have a sound working knowledge of statistics and the software selected to produce them.

Control charts may be inappropriate for some financial metrics—for example, examining financial indicators (*e.g.*, cost per student) where inflation leads to a continual upward trend.

When interpreting data in control charts, use caution when considering causality. Just because a tactic was implemented prior to a change in performance does not necessarily mean that the tactic caused the change. Sound knowledge of the research literature on a given topic, awareness of relationships between a desired performance outcome and other contextual factors, and understanding of the principles for establishing causation (Hill 1965) are essential.

Summary

Control charts can be used to improve the way in which decisions are informed by data in SEM and beyond. Compared to traditional means of visualizing data, control charts provide a complete set of indicators on baseline performance and allow the user to visually demonstrate improvement. Recognizing the three patterns in control charts makes it easy to see when performance has changed and when it has not. Using control charts to help set targets can provide decision makers with a realistic understanding of what is possible. Recognition of the three patterns in relation to a target indicates when to maintain performance, when to improve performance, and when to celebrate.

Application of control charts in higher education is relatively new; we have yet to realize their full potential. Possible uses abound, from board reporting, to monitoring SEM plans, to registration statistics. Using this method, decision makers can rely on data rather than a hunch.

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