Understanding the University of Virginia UPC Clinic Patient Flows Through Simulation Analysis

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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STS Research Paper

Introduction

The COVID-19 pandemic has caused unforeseen problems in many areas, especially the healthcare field. Hospitals faced increased patient influx that surpassed their possible capacity and forced them to reduce the quality of care. At the same time, the coronavirus pandemic forced many primary care facilities to move to telemedicine, causing a loss of revenue and threatening the survival of primary care clinics around the world. Located in Suite 2100 of the UVA Fontaine Research Park, the University Physicians of Charlottesville (UPC), a primary care clinic within the UVA health system, suffered from long patient wait times and a lack of nursing resources. However, in the process of emerging from the COVID-19 pandemic, UPC and many other clinics returned to their normal capacity. They adapted to face challenges and undertook measures to improve their operations.

In November of 2022, the primary care facility would see around 40 patients per day on average, with most days consisting of three to five nurses or doctors. This workload caused many nurses to report feeling overwhelmed and wanting some kind of reprieve. Simultaneously, the facility's management team wanted to add more patients for the nurses to see in a day. In February, management decided to increase the number of nurses to five, and it was the job of the capstone team comprising Harshal Patel, Emily Riggleman, Eric Nour, Aditi Jain, and me to show the management team whether or not to add the additional nurses has a significant impact on the primary care facility's operations.

Placing the UVA primary care facility into the broader context of the United States' nursing hiring market dynamics is not as difficult as it may seem at first glance. Instances of nurses feeling overworked and leaving their positions have become increasingly common across the United States and have led to increasing rates of nurse attrition (Haddad, Annamaraju, Toney-Butler; 2022). This rising rate of nurse attrition combined with the difficulty in transitioning back into pre-pandemic operations has hospital margins down 37 percent relative to their pre-pandemic levels, and more than half of all hospitals in the United States are projected to lose money in 2022 (Kaufman-Hall, 2022). Another factor that has been increasing costs for hospitals is the increase in the number of travel nurses. While a regular nurse normally costs around $1,400 a week, travel nurses are paid anywhere from $5,000-10,000 a week (Yang, 2022). Since some hospitals have trouble finding nurses with the rising attrition rates, they resort to hiring part-time travel nurses who cost more but can be brought in on an ad hoc basis to fill a hole left by nursing staff shortages. These compounding factors and the rural hospital closures occurring at an alarming rate even before the pandemic mean the healthcare industry faces many challenges (Kaufman, 2022). One of the best ways to alleviate these compounding problems facing United States hospital systems is to reduce the load on nurses through a more streamlined process. This new process should reduce the reliance on hiring travel nurses, allowing hospitals to return to profitability and remain open during this transition period.

Methodology

While there is no peer-reviewed literature on the UVA primary care system, research has been done on hospital queuing systems models at other universities. For example, a similar study has been completed at the University of Florida. Their hospital queueing system was modeled as shown in Figure 1 and had three different, independent arrival rates of λ_d, λ_f, and λ_a, where λ is in units of the number of people arriving per minute.

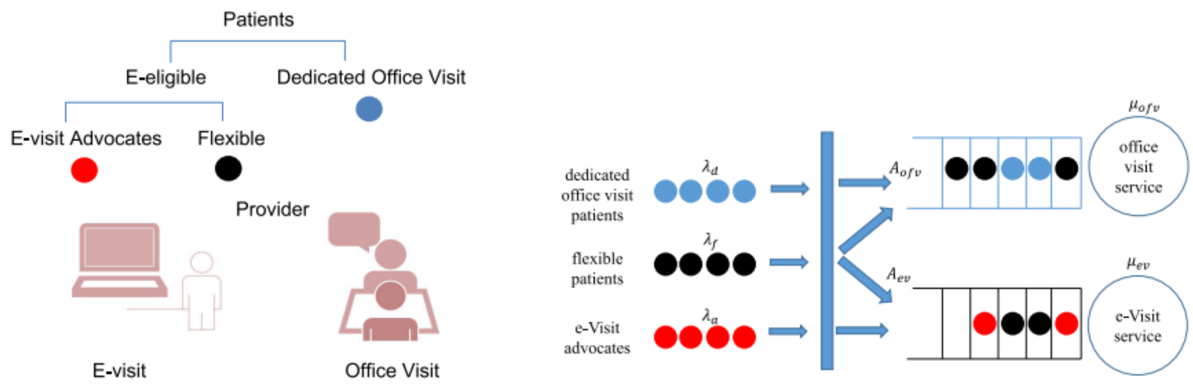

Figure 1. Patient Flow Diagram for the University of Florida Office Study

In their study, the three patients arrive at different rates, but each rate is modeled with the same distribution and underlying assumptions. These assumptions are that the arrivals are independent of each other (meaning the arrival of one patient does not affect the arrival of another), no patients arrive simultaneously, and that the probability of a patient arriving over one given interval versus the next is the same regardless of previous arrivals (Prakash, Zhong; 2022). These assumptions simplify the mathematical models, making the calculations for expected long-run behavior simpler. This research shows that these assumptions are valid for hospital systems. They can be used to simplify our calculations and help make the mathematical predictions for results and recommendations more precise. These more precise recommendations should help the UVA primary care facility make better, more informed decisions.

In addition to addressing the problem of how to build precise and usable mathematical models, the UVA primary care facility also faces the problem of data inconsistency and data interpretability that reduces the credibility of potential recommendations. The patient timing data was a black box in August of 2022. The company that the University of Virginia uses to compile the patient timing data does not disclose how it complies with important variables such as appointment time, time the patient is roomed, and time the visit ends. As a result, our team had to go in and make in-person observations on the times the nurse gets the patient, the nurse enters the room, the nurse leaves the room, and the patient leaves the room (all quantitative). We would then use this observational data to assess the validity of the black box data that the company provides to the primary care facility. After comparing the observational data to the data that the University provided, the group determined which variables are similar to the observed values. For example, after the final round of observations in November, it has been determined that the time that the black box system says that the nurse enters the room is when the nurse starts entering the patient meeting data into the system. Since the electronic patient process tracking system can take measurements for every visit, it provides a dataset an order of magnitude times larger than using strictly the observational data points the group collected in person. This ability to determine the precise problem with the data that was previously a black box has helped strengthen the recommendations since the group has more confidence in what the system metrics mean.

While the methodology our capstone group used involved in-person validation and cross-reference observations to the Epic system, other similar studies have used different and effective methods that could be used to determine the effectiveness of in-person validation. These methods might also be less time-intensive and, as a result, less expensive. For example, one study on the validation of multisource electronic health record data used a stepwise approach with expert feedback and literature on their topic to their data validity (Hoeven, 2017). Another such study in the journal Nature outlines a more strategic approach with a multi-step process for healthcare data validation and verification. The first step is called verification, and it involves evaluating the sample-level data against a pre-specified set of criteria. The second step is called analytical validation, and it evaluates the data's ability to predict. The third and final step is called clinical validation, and it involves evaluating whether the data predict a meaningful clinical outcome (Golsack, 2020). The capstone group's methodology for data validation better emulates the outline from the second study. The in-person verification matches the verification outlined in the first step, the mathematical model matches the second step, and the subsequent predictions from the simulation match the third step.

The capstone project has three major components. The first was data collection and validation whose steps are outlined above. The second phase consisted of a statistical analysis presented to the client in December 2022. The third and final phases of the model and simulation were presented to the client in March 2023.

Analysis, Results, and Comparisons

Analysis

The analysis presented to the client at the end of the semester presented various findings on topics she expressed wanting a deeper understanding of. For example, the presentations of the group's analysis included quantitative differences in delays based on the time of the day, delays based on appointment length, and length of appointment by the provider. The length of delays based on the time of day found that 65 percent of the patients at the facility were roomed after their designated appointment time, and afternoon appointments were more likely to be roomed later than morning. However, this difference was not statistically significant, so there cannot be any definitive statement made about how the time of day affects the time the patient is roomed at the UVA primary care facility.

In addition to analyzing how the time of day affects the proportion of patients who are seen before or after their appointment time, the group analyzed the patient rooming time by appointment length. As background, the UVA primary care facility has two different types of appointments: 20 and 40-minute. There are other appointment lengths as well but 20 and 40-minute appointments are the most frequent appointment types. The analysis found that the 40-minute appointments have a 43 percent chance of being brought to a room before their appointment time. On the other hand, 20-minute appointments have a 53 percent chance of being brought to a room before their appointment times. This difference ends up being statistically significant at a five percent threshold. Therefore, this result demonstrates an undesirable trait of 40-minute appointments that is not present with 20-minute appointments. However, this difference does not mean that 20-minute appointments are superior since there are likely other factors at play. For example, the 20-minute appointment time could have a higher probability of being on time since there is more likely a 40-minute appointment before it, meaning the nurses are not as rushed and are more likely to room the subsequent appointment on time. Additionally, the people who tend to need 40-minute appointments are more likely to be elderly, requiring assistance accessing the building, causing them to arrive later to the appointment. It could also be the case that nurses feel a higher priority on rooming 20-minute appointments on time since there is a greater sense of urgency to bring them to a room if the primary care facility is to remain on schedule.

The third piece of the analysis was the difference in room times for different care providers. As seen in Figure 2, most of the providers had similar distributions for their room times, except for one.

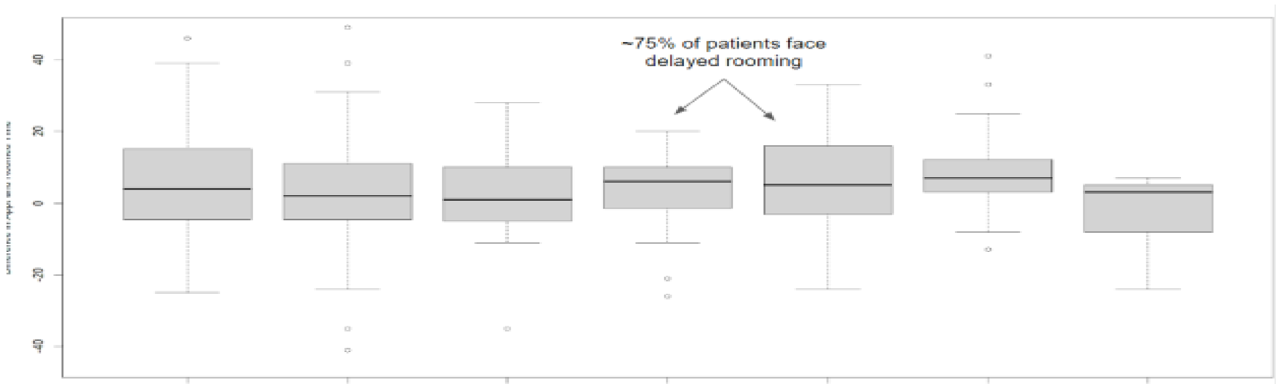

Figure 2. Boxplot of room times by Provider

However, this reduction in the average room time for just one provider does not result from the provider taking a shorter time with their patients or nurses. Rather, it results from a small sample size since this provider only had a handful of observations (5-6) over that week, while the other providers had dozens. Removing this provider from the analysis in Figure 3, it becomes evident that there is no major difference between room times by the provider.

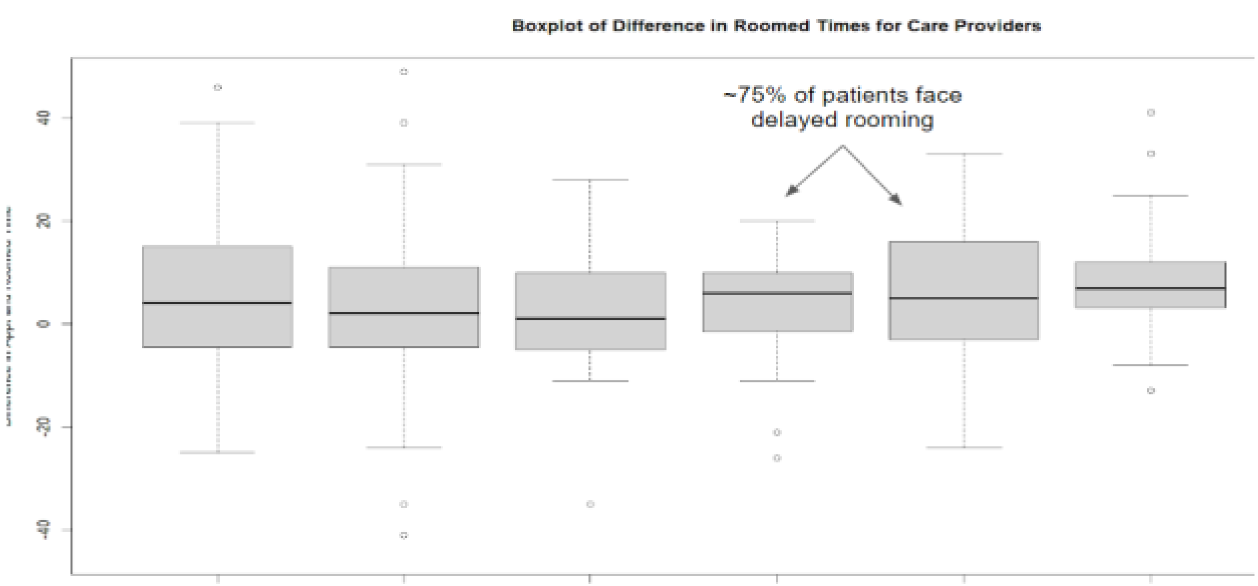

Figure 3. Room times by Provider (removed outlier)

The final major piece of the analysis presented to the client in the December meeting remains the data validation and final assessment of what triggers each metric in the Epic data system that was previously a black box. The revelation that the observational time when the nurse starts inputting data into the system matches when the system creates a time stamp called "nurse enters." This matching of the observational and Epic data was completed using the observational appointment date and time, and the nurse entering the patient data as the key to match the data present in the pre-existing black box epic system, which simply has the variable "nurse enters" in a data file without any explanation of what triggers that time stamp. This analysis and validation assist with the next steps of generating simulation results and recommendations for the primary care providers on what the best changes are to make to improve patient flow.

Results

The simulation was utilized to compare various what-if scenarios. These scenarios were determined based on the needs of the client and the inefficiencies we had seen when observing the clinic. The main factors explored with the simulation were the ratio of nurses to providers and the number of patients a provider would see in a given time frame.

At the beginning of this research, the clinic was operating at suboptimal nursing levels, where they had a maximum of three nurses staffed. Throughout the time the team has spent with the clinic, they have increased their staff to five nurses. The fifth nurse is leaving the clinic as of the writing of this paper. As a result of this change, the team was curious if there was significant justification for hiring another nurse to retain a nursing level of five. The simulation was utilized to explore the optimal ratio of nurses to providers. It was found that an optimal level is an equal number of nurses and providers, but the clinic can operate sufficiently with one less nurse than the provider. This is suboptimal but does not increase cycle times by more than 25% as seen when comparing Figures 4 and 5.

The simulation was also beneficial in exploring the necessity of a cap on how many patients a provider can see in a session. The sessions are defined as a four-hour time block in the morning and afternoon, where there are two sessions per day. Administrators are pushing for the clinic to increase the number of patients they are seeing per session. According to historical data from December and January, providers are currently seeing an average of eight patients per four-hour session. Increasing this number of patients per session to twelve will increase patient cycle times by 35-50% as seen when comparing Figures 4 and 5.

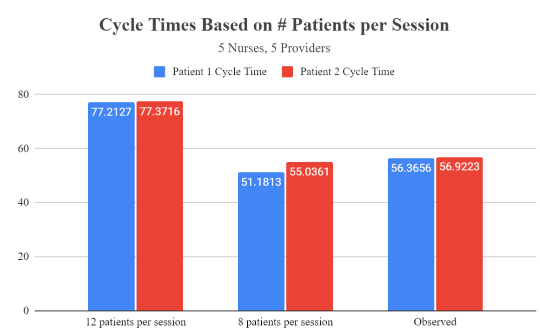

Figure 4. Cycle time (5 N, 5P)

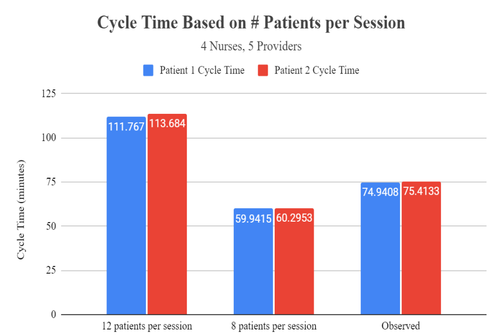

Figure 5. Cycle Time (4 N, 5P)

Suppose the results from this simulation experiment match the February data of five nurses and five providers. In that case, the group will conduct other experiments under "what-if" scenarios, testing different hypotheses the client has for the team. These results would then help the client and the UVA primary care facility predict which changes would have the most positive outcomes, hopefully leading to a lower-stress and more efficient primary care facility where the patients receive the care they need. Additionally, these results could help the nurses and providers feel that their workload is sustainable and that their time is being used to its fullest potential, setting an example for other primary care facilities across the nation.

Comparison

Many of the healthcare simulations conducted in larger-scale studies involve multi-year processes and are incredibly complex. For example, one study conducted for the Department of Pediatrics said, “A formal needs assessment applying strength weaknesses opportunities and threats (SWOT) analysis. . . These brainstorming sessions and in-person interviews guide clinical leaders and frontline staff to identify high frequency/low acuity events (e.g., routine admissions) and low frequency/high acuity events” (Coleman, 2019). While sometimes warranted, this in-depth analysis simply did not fit into the time frame of the client, so it was omitted from the process. A different journal article also went more in-depth than the extent of the group’s simulation when they created a simulation protocol to evaluate a healthcare system facility’s efficiency by its layout. The study then used a matrix of different simulation techniques compared to its level of detail and showed that simulation as a technique is extraordinarily useful when predicting a healthcare facility’s efficiency based on its layout (McClure, 2016). The results from this healthcare simulation show that the simulation as a tool is not only useful for manufacturing processes but can also be used in healthcare settings like that of the UVA primary care facility.

In addition to the aforementioned study that showed that a simulation is a useful tool when analyzing healthcare systems, other studies have shown that its rate of use is increasing. The research paper “Simulation Modelling in Healthcare: An Umbrella Review of Systematic Literature Reviews,” demonstrates that there have been more studies over the past few years involving simulations in the healthcare sector (Salleh, 2017). Another study that demonstrates this trend simulated a primary care facility in great depth. Figure 5 shown below gives the distributions, values, methods, and parameters for each part of the study’s simulation, similar to how the simulation our group constructed used various distributions with different values for means, minimums, and maximums for building the most appropriate distribution (Shoaib, 2022). For example, the distribution of the time in a room with the nurse in the simulation is given a lognormal distribution since that was found to have the closest adherence to the distribution shown in the data. So, this method for distribution, value, and parameter creation of the simulation for the UVA primary care facility matches that of a previous study conducted at the primary care facility in Delhi, India in Figure 5 below.

Table 4. Facility independent input parameters.

Parameter	Value (min)	Probability distribution	Method
Doctor (OPD) consultation time	Mean = 0.87, SD = 0.21	Normal	Data collection (stopwatch)
Pharmacy service time	Mean = 2.08, SD = 0.72	Normal	Data collection (stopwatch)
Laboratory service time	Mean = 3.45, SD = 0.82	Normal	Data collection (stopwatch)
Nurse (NCD check) service duration	Min = 2, max = 5	Uniform	Data collection (nurse discussion + limited observations collected)
Doctor (inpatient) service time	Min = 10, max = 30	Uniform	Data collection (doctor discussion)
Nurse (inpatient) service time	Min = 30, max = 60	Uniform	Data collection (nurse discussion)
Nurse (childbirth) service duration	Min = 120, max = 240	Uniform	Data collection (nurse discussion)
Inpatient bed length of stay	Low = 60, high = 360, mode = 180	Triangular	Data collection (doctor and nurse discussion)
Labor bed length of stay	Min = 300, max = 600	Uniform	Data collection (doctor and nurse discussion)
Doctor (childbirth) service time	Min = 30, max = 60	Uniform	Data collection (doctor and nurse discussion)
Childbirth patient bed length of stay	Min = 240, max = 1440	Uniform	Doctor and nurse discussion, IPHS guidelines[10]
ANC visits	Four visits	Deterministic	IPHS guidelines[10]

ANC: antenatal care; NCD: noncommunicable disease; IPHS: Indian Public Health Standards; OPD: outpatient department.

Figure 5. Indian Primary Care Facility Parameter Values and Distribution Table

Another paper used what it calls “agent-based” models to simulate system dynamics of health systems. This paper found that future work in the area of health system modeling should be going to middle and low-income countries. The authors made this claim because the vast majority of papers like this one modeled health systems in upper-income countries, neglecting lower and middle-income countries (Singh, 2019). Going forward, students at the University of Virginia and hopefully more could combat this inequality of healthcare modeling by using the skills they have learned modeling health systems in wealthier countries to help improve the operations of hospitals in developing nations.

Limitations

Although some papers have documented the benefits of simulations, others present and note their drawbacks and limitations. For example, one such paper on simulation methods similar to the results the group hopes to present models the skill training in healthcare logistics. This paper addressed the limitations of simulation and found that system-level and complex systems-based approaches necessitate methods other than simulation as a result of their inherent complexity (Zhang, 2018). Another paper argues against simulation in favor of returning to experimentation. In his paper, Knippers argues for a return to 19th-century style experimentation since physical testing is needed to overcome the limitations of simulations set by their prerequisite boundary conditions (Knippers, 2017). In his paper on complex adaptive systems, Tolk argues that computer simulation falls short, saying "Computer representations of complex adaptive systems are limited, as claims to produce systemically real emergence with computational systems contradicts some fundamental insights from computer science and philosophy of science." This passage shows that simulation is limited to self-governing, complex adaptive systems (Tolk, 2019). While a small primary care facility may not exhibit all the traits of a complex adaptive system, larger healthcare systems likely will. Therefore, the inability of simulations to produce the emergence effects found in complex adaptive systems limits attempts to expand the results from this paper to larger health systems.

For the limitations of our analysis itself, there were instances where the data time stamps did not accurately represent the appointment. For instance, there was a data point where the cycle time was 2 minutes, which is impossible. We needed to remove outliers to perform data analysis. This removal of outliers meant that the simulation validation was limited to a small subset of the days rather than the entire dataset, resulting in less confidence in the final results.

The length of patient visits also likely has large seasonal components with appointments lasting longer in the Fall due to flu season. However, the group collected simulation data from November and February since they had differing numbers of nurses in the facility. This time-of-year discrepancy for the simulation data may have caused a difference in appointment lengths and resulted in less confidence in the final results.

Conclusion

The University of Virginia is currently reassessing its UPC clinic at Fontaine Research Park coming out of the coronavirus pandemic. While this presents a significant challenge, it also brings opportunities for improvements to the system as well. By comparing our study to similar ones done at different universities and learning from their mistakes and innovation, our group can offer an ideal solution for the UVA primary care system. One such solution is that the University of Virginia is considering adding a permanent fifth nurse to the primary care facility, which our group showed had a significant effect on patient wait times. These potential changes are viewed differently by all of the different stakeholders, and their societal consequences of them can be severe. Therefore, when presenting our final technical analysis and recommendations, our group should also ensure to mention the elements of uncertainty that underlie any stochastic analysis.

Our recommendations could have a large effect on various key stakeholders in addition to the patients themselves. Therefore, in the next steps of this analysis, we must consider the needs of all of the different possible users of the system. We must also consider the limitations of simulations and the fact that simulations are always built on a dataset comprising only past events. As an example, the simulation would have been unable to predict how the primary care facility should react three years ago when the coronavirus pandemic was first starting to spread in the United States, and many Americans were justifiably afraid to go outside (Wagner, 2021). It is precisely in these extraordinary, unpredictable, and unprecedented events and situations that the response matters the most, and simulation fails to have the answers. This fact makes acknowledging these shortcomings of simulations and what-if scenarios the group has built essential to the success of the project. While simulation and statistical analysis remain useful tools in a system's engineer's arsenal, they should not substitute for additional qualitative analysis and acknowledgment of risks to ensure that all patients receive the care they need. This discrepancy is especially in times that do not match the historical trends the simulations are built upon. All of these previous facts and limitations being made evident, the simulation's final recommendations to the UVA primary care facility will not only be data-driven, but they will also note the potential dangers and risks associated with the suggested change if something outside of the expected data set were to happen. In conclusion, the final recommendation for my group's capstone project remains to keep four or five nurses working in the clinic at all times. However, it should be noted that external events outside of the control of those at the UPC clinic could change that recommendation as historical trends are not always indicative of best future practices.

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