Application of Simulation Techniques in Child Welfare Case Rates

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September, 1999

Background

The use of case rates in managed care contracting seems to be on the increase with increasing numbers of organizations, from small practice groups to large child welfare organizations, are reporting case rate contracts. As with other types of risk-based financing arrangements there are significant opportunities for success as well as failure. Groups and organizations with little or no experience in risk-based contracting should seek the advice of a professional when considering such an opportunity. This paper summarizes the application of statistical simulation techniques to case rate models in order to quantify the level of risk involved in the rate. Hopefully, this will assist child welfare organizations in making more informed choices as these financing methods are deployed in the field.

The Basics of Case Rates

A case rate is consumer-based. A new case rate is paid for every new client referred. A case rate can also be referred to as "contact capitation"

Capitation is population-based, regardless of the number of clients or services required

First, case rates should be differentiated from other types of risk-based financing methods, principally capitation. Simply defined, a case rate is a stipulated dollar amount established to cover the cost of a defined set of services delivered for one person or "case" during a specified period of time. The term usually refers to a negotiated rate to be paid for each client (or family) referred for service. The amount is usually paid up front for the cost of care for that client/family for a defined period of time, usually a year, and typically no additional payments are made. Case rates are referred to as "consumer-based" payments.

On the other hand, capitation is a stipulated dollar amount established to cover the cost of healthcare services delivered for a population group. The term usually refers to a negotiated per capita rate to be paid periodically, usually monthly, for the delivery of all health service required by the covered group under the condition of the provider contract. The payment is the same regardless of the number of clients served or the amount of service rendered during the contract period. For this reason, capitation is referred to as a "population-based" payment.

The primary factors to consider in a case rate calculation are as follows:

- Cost per unit of service, by discipline, service, or program
- Average "mix" of disciplines/services/programs needed to treat the "average" client for the diagnostic group or other client grouping to which the case rate will apply
- Average number of services needed to produce the outcomes required by the payer

Obviously, a provider organization needs to have a thorough understanding of the following items:

- Internal cost structures and cost drivers by service type, level of care, and provider/program
- Practice patterns by provider/program
- Effectiveness by provider/program
- Ability to triage and case manage clients under case rates
- Ability to monitor severity and produce reports based on this data

Following is an example of a very simple case rate calculation:

Items	***Variable***
Members	92,000
Penetration	1.7%
Total Cases	1,534
Total Visits	9,202
ALOS per Case	6
Cost per Visit	$75
Average Cost per Case	**$450**

As illustrated, the calculation of an average cost per case is not dependent on the number of "covered members" and the penetration rate. These factors have a secondary effect on the calculation in that they may serve to indicate volume, which may allow the provider group to do the following:

- Alter the cost per visit to account for volume-based considerations.
- Design new interventions, such as specialized groups, that are possible only with a certain level of volume.

Following is an example of a more complicated case rate that involves multiple levels of care and estimates of the percentage of cases that may require certain services:

SERVICE	UNITS	COST	GROSS COST	WEIGHT	ULTIMATE COST
Foster Care Maintenance	3	800	2,400	100.00%	2,400
Mental Health					
Outpatient	35	75	2,625	60.00%	1,575
Outpatient MD	6	100	600	30.00%	180
Residential	6	5,000	30,000	16.67%	5,000
Inpatient	3	450	1,350	3.33%	45
Day Treatment	180	150	27,000	8.33%	2,250
Transportation	52	15	780	100.00%	780
TOTALS			**$64,755**		**$12,230**

As one can imagine, the complexity of these models can grow significantly as more and more services are included in the case rate.

Variability and Risk in the Model

In most cases, a provider organization is subject to two primary types of risk in a case rate:

- Beta Risk, or the risk that the cost of one case may vary from the mean or average cost. This type of risk becomes negative when a provider experiences adverse selection (exposure to a particularly difficult population when the rate structure is calculated for a "typical population.")
- Price Risk, or the risk associated with the accuracy in calculating the cost of an individual unit of care. For cases requiring a mix of providers with different cost structures, the provider group must develop a weighted average cost per unit.

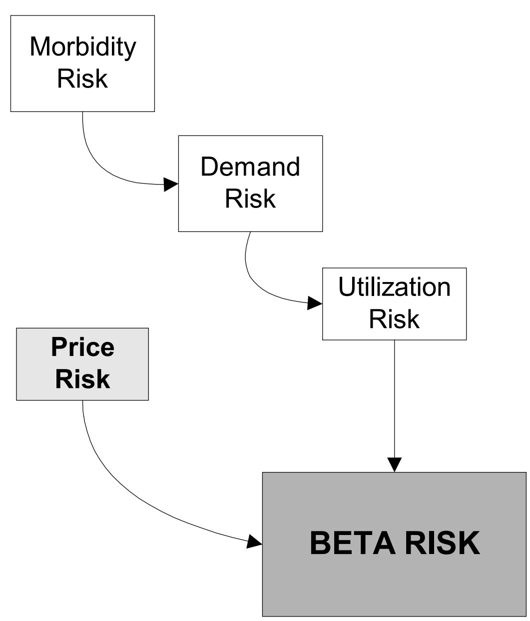
As the level of complexity increases, such as in many child welfare case rate structures, different types of risk begin to affect the beta risk. These other types of risk are defined as follows:

- Morbidity Risk, or the relative intensity of service need. This differs from utilization risk because it is based on the actual amount of "sickness" (morbidity) in the population. It addresses "How many severe bipolar disorders will there be in this population?" rather than, "How many sessions it takes to treat a severe bipolar disorder?"

- Demand Risk, or the risk that the "covered lives" or cases demand more service than expected. Demand risk is different than utilization risk (the amount you provide for clients) or morbidity risk (the amount of care that clients need). Rather demand risk is based on the desires of the clients served, and it can be influenced by provider marketing programs, governmental case management preferences, etc.

- Utilization Risk, or the risk that the actual amount of care or services delivered to a population or case differs from that expected. Utilization risk is influenced by average lengths of stay, average visits per case, and use of levels of care. Negative utilization risk occurs with clients receive significantly more care than estimated.

The relationship between these types of risk can be illustrated in the following chart:



Most organizations tend to construct these models in spreadsheets, using single-point estimates for the variables involved to arrive at an estimated rate. What is usually missing from these models is a calculation of the probability of that single point estimate actually occurring along with an estimate of the degree of risk involved in each of the variables and in the final estimate.

Limits of Spreadsheet Models

Using the second case rate model illustrated earlier, the following variables can be characterized as "uncertain":

- The number of units of service used by a case
- The cost per unit of service for each service type
- The "weight" or the proportion of cases that will use each service outlined

Once we have reached this point in our model construction and recognize the potential variability in the estimate, we are faced with a common dilemma: What values do we change and what are the probabilities of those values occurring in real life? In other words, how do we know our estimate is valid, and what is the nature and extent of the risk involved for our organization?

We typically answer these questions using a variety of single-point variations in the model, i.e. we change the value of one cell and see the effect on the target value (The "Ultimate Cost" in our model). We can go a step further and construct "worse case", "most likely case", and "best case" scenarios. But again, this limits us to three likely outcomes, and we are still missing a measure of the degree of risk involved and the probability of any of those cases occurring.

We are still faced with a substantial obstacle: How many changes and what changes do we make for the variables? In our model, for example, it would be impractical to substitute a variety of different possible values for the "outpatient regular visits" variable in order to see the outcome on Ultimate Cost. This type of single-cell input is impractical for all the variables in the model. Although it might be physically possible to substitute a large number of values for each variable, it quickly becomes practically impossible to track the effects of each change on the target cell, Ultimate Cost.

David T. Hulett succinctly states the problem: "Future estimates are not facts but statements of probability about how things will turn out. Because estimates are probabilistic assessments, costs may actually be higher or lower than estimated even by seasoned professional estimators. The reasons are often causes that are outside the control of the project manager, but may also be endemic to the estimating process, the project strategy or the corporate culture within the project contractor."[1] In other words, costs may vary significantly from the estimate no matter how experienced or informed the estimator may be.

Using Simulation Techniques

The use of simulation techniques allows us to directly address the probability features of a case rate estimate by conducting a large number of "what ifs" on each uncertain variable in the model. In short, it allows us to perform a cost risk analysis. This type of analysis allow us to answer the following questions:[2]

- "What is the most likely cost?" The traditional method assumes that this is computed by summing the estimates of cost for the various levels of care. In actuality, all it produces is one possible outcome among many.

- "How likely is the baseline estimate to be overrun?" Traditional methods do not address this problem. Although we can guess at other outcomes, traditional spreadsheet models do not allow us to estimate the **probability** of each of those outcomes actually occurring.

- "What is the cost risk exposure?" This is also the answer to the question; "How much contingency do we need on this project?" For case rate projects, the question would be: " What is the correct amount of reserves to set aside for potential cost overruns?" Again, using traditional spreadsheet models, we can guess, but we can't quantify the uncertainty.

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[1] "Project Cost Risk Analysis Using Crystal Ball©," David T. Hulett, Hulett & Associates, Project Management Consultants, 12233 Shetland Lane, Los Angeles, CA 90049, (310) 476-7699 and info@projectrisk.com
[2] Ibid.

- "Where is the risk in this project?" This is the same as: "Which cost elements cause the most need for the contingency?" Traditional spreadsheet models are not suited to answer this question using reasonable time and resource limits. Risk analysis principles and simulation can be used to answer this question.

Use of simulation techniques in rate setting is recognition of the variability inherent in the "uncertain" variables in the model. The quickest and most efficient way to perform these analyses is through the use of simulation software. This example will use Crystal Ball© by Decisioneering, Inc. to illustrate the advantages of these techniques.

Additional Data Requirements

All risk estimation techniques are based on probability distributions. A probability distribution describes the likelihood of specific values occurring out of a range or set of values. If the range of values is limited to certain values, the probability distribution is said to be discrete. If the range of values contains an infinite set of possible values, the distribution is said to be continuous.[3]

Depending upon the nature of the data, there are a variety of probability distribution types that can describe the data. The two most common distribution types that "fit" child welfare data include:[4]

- **The Triangular distribution:** The triangular distribution shows the number of successes when you know the minimum, maximum, and most likely values. For example, you could describe the cost per outpatient social work visit when past cost data show the minimum, maximum, and most likely costs. It has a continuous probability distribution.

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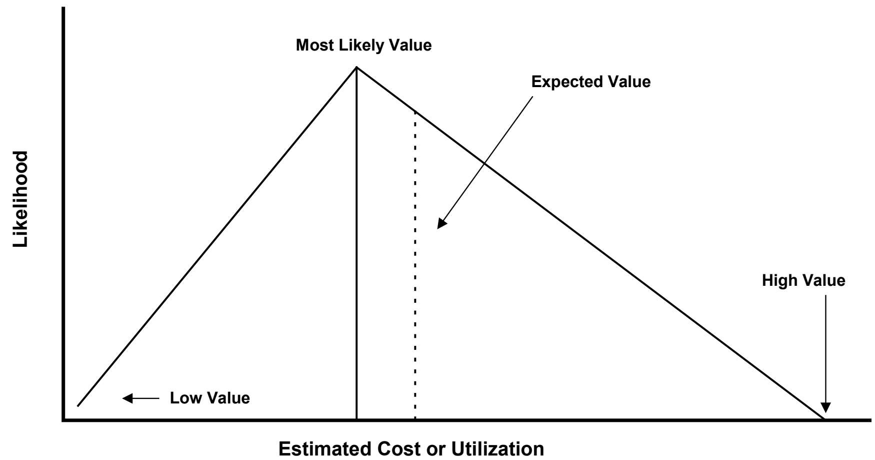
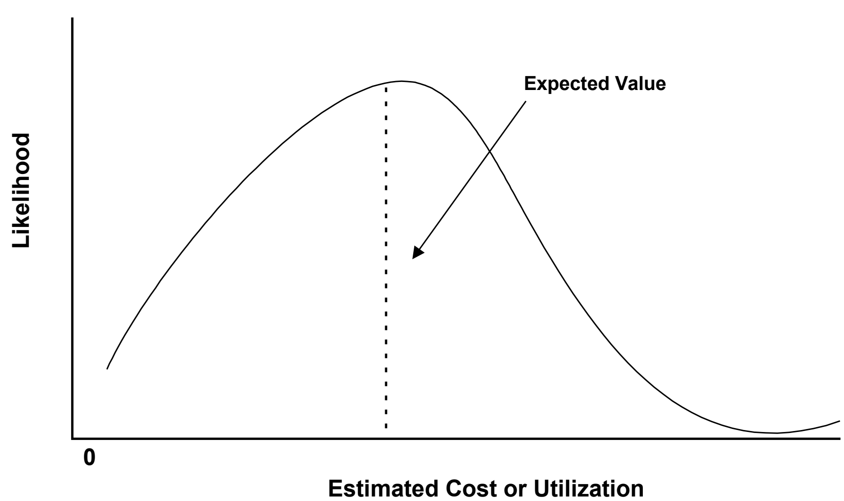
3 Crystal Ball© glossary.
4 Ibid.

The triangular distribution can be illustrated as follows:



- **The Lognormal distribution:** The lognormal distribution is widely used in situations where values are positively skewed (where most of the values occur near the minimum value). It has a continuous probability distribution. Healthcare costs illustrate positive skewness since the number of services or the cost per service cannot be negative. For example, there can't be negative cost for services in a case rate contract. This distribution accurately describes most healthcare data. The parameters for the lognormal distribution are Mean and Standard Deviation. The lognormal distribution can be illustrated as follows:



Other distribution types not discussed in this paper include:

Binomial	Beta	Custom
Exponential	Extreme Value	Gamma
Geometric	Hypergeometric	Logistic
Negative Binomial	Normal	Pareto
Poisson	Uniform	Weibull

In order to describe the distribution types of the "uncertain" variables in our model, we need additional data about the uncertain variables. There are several sources for this additional data:

- Analysis of Historical Data: If an organization has historical data describing an uncertain variable, a simple analysis will yield the parameters of the underlying distribution, such as the mean and the standard deviation.

- Interviews with Experts: In those cases where historical data is unavailable or unreliable, additional information may be obtained from interviews with staff or other experts. This is particularly applicable for descriptions of data that fit a triangular distribution. As Hulett states, "(Interview) participants can describe and estimate the low, most likely and high range estimates."[5]

- Proxy Estimates: Proxy estimates refer to the use of similar data sets. These can often be obtained from consulting firms specializing in claims data analysis and risk-based rate estimation. In child welfare, data from another county or state may be a realistic substitute when primary historical data is unavailable or unreliable.

Once an organization is able to describe the likely distributions of the uncertain variables, simulation techniques can be employed. We will employ the Monte Carlo simulation technique as used in the Crystal Ball© software[6]. This technique employs a series of random numbers, constrained by the distribution parameters chosen, to manipulate the risk estimation model and the resulting effect on the

[5] "Project Cost Risk Analysis Using Crystal Ball©," David T. Hulett, Hulett & Associates, Project Management Consultants, 12233 Shetland Lane, Los Angeles, CA 90049, (310) 476-7699 and info@projectrisk.com

[6] For a brief discussion of the different sampling methods employed in simulations, see the paper entitled "Simulation Techniques for Risk-Based Financing Estimates in Behavioral Health Managed Care" by the author.

target cells – the Ultimate Cost. This technique can accommodate models such as ours that have a large possible number of "what-ifs" that would be impractical to manipulate on a case-by-case basis. As an example, the process can conduct up to 10,000 trials – or "what ifs" – on each assumption cell using the parameters defined in the underlying distribution. As Hulett states, "A Monte Carlo simulation "solves" the problem many times. Each solution is called an iteration. For each iteration, the simulation program selects a cost (or utilization parameter) at random from the probability distribution specified by the analyst for each uncertain cost (or utilization) element."[7]

Using our complex case rate model, we will define a small number of uncertain variables as follows:

Assumption: Foster Care Maintenance Cost

Triangular distribution with parameters:

Minimum	650
Likeliest	800
Maximum	1,000

Selected range is from 650 to 1,000
Mean value in simulation was 816

Assumption: Foster Care Maintenance Units

Triangular distribution with parameters:

Minimum	2
Likeliest	3
Maximum	6

Selected range is from 2 to 6
Mean value in simulation was 3

Assumption: Outpatient Regular Units

Lognormal distribution with parameters:

Mean	35
Standard Dev.	12

Selected range is from 0 to +Infinity
Mean value in simulation was 35

Assumption: Outpatient Regular Cost

Triangular distribution with parameters:

Minimum	55
Likeliest	75
Maximum	95

Selected range is from 55 to 95
Mean value in simulation was 75

[7] Ibid.

Assumption: Outpatient Regular Weight

Lognormal distribution with parameters:

Mean	60.00%
Standard Dev.	25.00%

Selected range is from 0.00% to +Infinity

Mean value in simulation was 59.69%

Assumption: Inpatient Units

Lognormal distribution with parameters:

Mean	3
Standard Dev.	2

Selected range is from 0 to +Infinity

Mean value in simulation was 3

Assumption: Inpatient Unit Cost

Triangular distribution with parameters:

Minimum	350
Likeliest	450
Maximum	650

Selected range is from 350 to 650

Mean value in simulation was 484

Assumption: Inpatient Weight

Lognormal distribution with parameters:

Mean	3.33%
Standard Dev.	1.00%

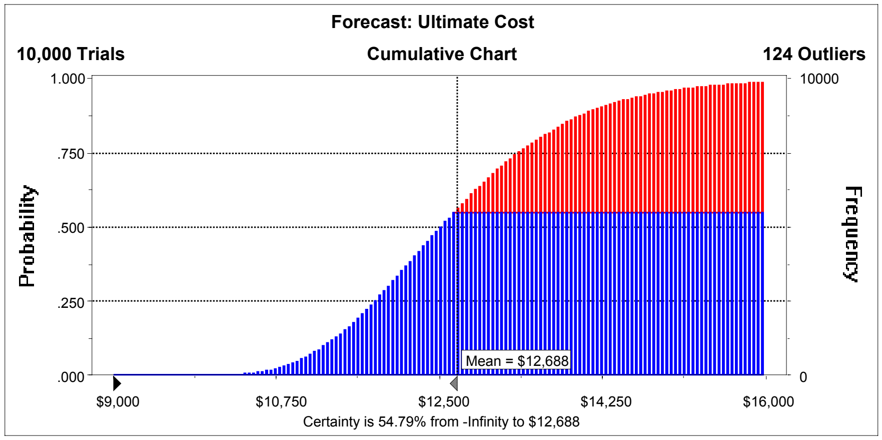
Selected range is from 0.00% to +Infinity

Mean value in simulation was 3.34%

These cells are highlighted in the following table:

SERVICE	UNITS	COST	GROSS COST	WEIGHT	ULTIMATE COST
Foster Care Maintenance	3	800	2,400	100.00%	2,400
Mental Health					
Outpatient regular	35	75	2,625	60.00%	1,575
Outpatient MD	6	100	600	30.00%	180
Residential	6	5,000	30,000	16.67%	5,000
Inpatient	3	450	1,350	3.33%	45
Day Treatment	180	150	27,000	8.33%	2,250
Transportation	52	15	780	100.00%	780
TOTALS			**$64,755**		**$12,230**

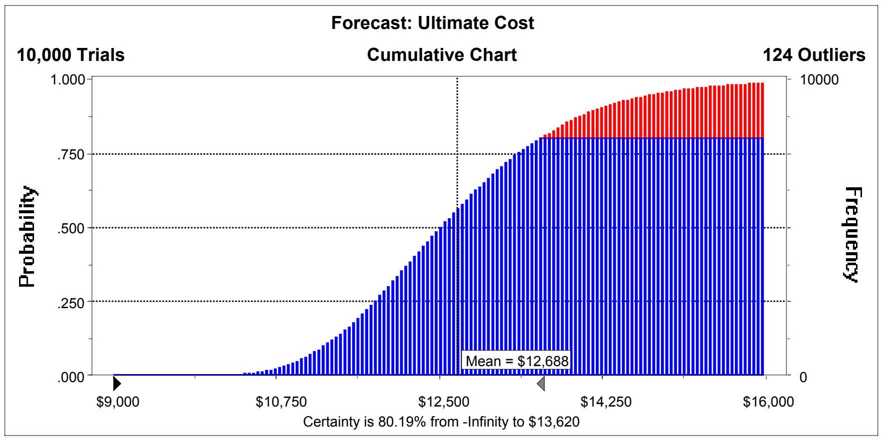
Given these assumptions about the uncertain variables, a 10,000 trial simulation produced the following results:



What we can learn from the simulation are the following key points:

- The estimated mean cost per case, given the parameters set for the uncertain variables, is $12,688.
- Again, given the underlying characteristics of the uncertain variables, we have a 54.8% chance of the per case cost falling at or below the mean. In other words, we have a 45.2% chance of the cost per case exceeding the mean.

Most child welfare organizations would not accept a 54.8% chance of success. If we were to achieve a higher probability of success, we would need a higher case rate. Using the simulation tool's output, we can specify the probability level we desire and let the model calculate the necessary case rate. For example, if we wanted an 80% chance of success, the model would produce the following results:

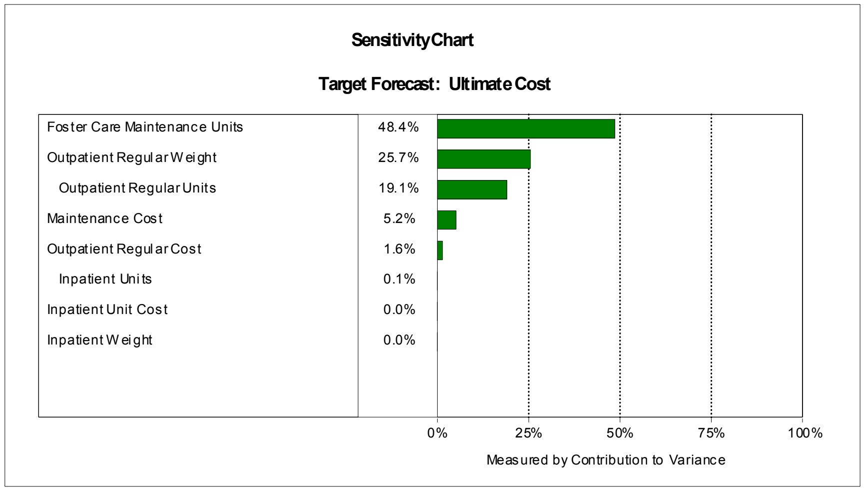


To achieve the 80% probability of success, a case rate of $13,620 would be needed.

Determining the Risk in the Model

Simulation can be used effectively to determine the nature of the risk inherent in the model through the use of sensitivity analysis. A key output of these simulation techniques is the identification of the specific variables that have the greatest effect on the outcomes of the model. We can rank the variables by their contribution to risk in the model. This analysis allows an organization to focus analytical resources on those uncertainties in the estimate that matter the most.

For our sample model, the sensitivity analysis is as follows:



Of the eight uncertain variables defined in the model, a sensitivity analysis points to the following three variables as those most likely to contribute to variance from the mean cost per case.

- Foster Care Maintenance Units contributes to 48% of the model's variance

- Outpatient Regular Weight, or the estimated proportion of cases requiring this intervention, contributes 26% of the variance

- Outpatient Regular Units, or the average number of visits per case, contributes 19% of the variance.

All together, these three variables contribute to over 93% of the variance in the model. Thus, they should be primary targets for clinical improvement and management and should become "key indicators" for the project. Additional planning and discussions with clinical leadership can often yield strategies for control of these important variables. Because of their importance, the organization can devote additional analytical resources to the data that produced the underlying distributions. Perhaps another data set can be acquired, allowing the distribution parameters to be refined, and therefore increase the accuracy of the model.

Overall, this type of sensitivity analysis allows an organization to focus resources on those variables that matter the most in the model and the ultimate outcome – the Ultimate Cost per case.

Summary

This paper has outlined the relative advantages of using simulation techniques in the development and evaluation of case rate pricing proposals. Traditional spreadsheet models that rely on single-point cost and utilization estimates do not furnish adequate information on the potential risk involved. Using simulation software such as Crystal Ball©, we were able to calculate a large number of “what ifs” on each uncertain variable defined in the model.

In addition, we were able to identify those variables that contributed significantly to the risk inherent in the model, thereby increasing our effectiveness in both estimating the final rate and ultimately managing the results. Using simulation, an organization can gain critical knowledge about the reasonableness of case rates, and the nature of the risk involved in a case rate model.

The sample used in this paper is a simple reproduction of complex financial models used in actual rate estimates. An actual model would involve a larger number of variables, and an organization should be prepared to devote sufficient resources to data gathering and analysis in order to ensure that these methods produce reliable data.

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