Human Cognitive Performance Data Analysis

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April 12, 2025

# Abstract

Human cognition is a crucial portion of a well-functioning individual. Many factors play a role in the deterioration or nourishment of cognitive performance. Thus, it is important to understand and research what these factors are. In the growing age of technology, cognitive performance has been dramatically affected positively or negatively by constant screen time and media consumption (Stenberg et al., 2013). This research focuses on uncovering how habitual activities such as diet, exercising, and sleep may affect cognitive function. Furthermore, to analyze these issues, we approach the problem via performing statistical analysis on a real-world dataset, called “Human Cognitive Performance Analysis” by Samx\_sam from Kaggle. The dataset contains various information about individuals and their health statistics. Through this experiment, we can analyze and predict the possibility of cognitive performance as well as demonstrating the usage of statistical methods to learn about the dataset.

# Introduction

Human Cognitive Performance is a metric in evaluating the ability to process, understand, and respond to information. This metric varies from individual to individual primarily affected by their lifestyle. Lifestyles can greatly influence cognitive performance positively when monitored and balanced. But it can also deteriorate this performance.

A common problem in the modern age workforce is the damage in circadian rhythms due to overnight work (Chellappa et al., 2018). For example, according to Chellappa et al., “a cognitive slowing was observed under circadian misalignment with median reaction times of ~300 ms when assessed 11h after scheduled awakening” (2018). This shows that even during work, especially for some, cognitive performance can greatly influence daily life. This is crucial, especially for growing children, as media consumption and screen time have overall increased which can affect their learning and attention. Lifestyles are only one of the few factors that can deteriorate cognitive performance, many other factors play a role such as eating habits, exercise, and sleep.

Through this study, we will analyze various health information of multiple individuals collected as a large dataset. We will perform multiple statistical methods such as: histograms to visualize an overall distribution of health information, probability of having certain cognitive performance score given a condition, and much more. This study’s goal is to perform as many statistical methods as possible in various question formats to understand human cognitive performance and the effects of certain factors in determining their scores.

# Methods

To understand the dataset, it is important to visualize what the data looks like. To do so constructing a relative frequency histogram allows us to quickly view how the data is distributed. For the dataset being used, we specifically focused on the percentage of occurrences for each specific column of data. This is possible via graphing the data in Excel using a pivot table and adding the selected column to the rows and values. Values will be change to “Count”. Once done, we can construct a pivot chart for our data. Finally, we can change how the value is presented as “% grand total”. This was done for all the 12 columns (ignoring the unique ID as it serves only as an identifier).

Once the histograms for each column of the dataset were found, it was important to further analyze what these graphs are informing us. To do so we needed to find the mean, median, mode, variance, and standard distribution for each graph. We did so via the built-in Excel functions (AVERAGE, MEDIAN, MODE. SNGL, VAR.P, and STDEV.P), categorical data will be ignored as Excel limits these functions to numerical data only.

One area we focused on to understand how cognitive performance is affected is through an individual’s sleep duration. In the following experiment, we tried to predict the chances of an individual being sleep deprived. Sleep duration for individuals is approximately distributed with mean = 7.01 and standard deviation = 3.01. What fraction of all individuals would have sleep deprivation in the following intervals: 4.00 to 10.02 hours? 0.99 to 13.03 hours? 4.00 to 16.04 hours? Less than -2.02 or more than 16.04 hours? We can find these answers via simply finding the empirical rule and discerning the common standard deviations.

Another way of constructing our understanding of the distribution of the data is through set notation. An individual has noted their gender, diet type, and exercise frequency. Let F denote female and M for male. We can denote NVG for non-vegetarians, VGN for vegetarians, and VEN for vegans. Then we can also denote L for low exercise frequency, M for medium, and H for high. Construct a space S. Find A, the following subset of possibilities containing no vegetarians, B the subset containing a female, and C, the subset containing a vegetarian. List the element of A, B, C, A B, A B, A C, A C, B C, B C, and C . We can find these answers by simply finding every combination of our data. Then performing the set operation given.

An important aspect in statistical analysis would be learning what the probability of occurrences would be. In our dataset we can learn, for example, what the probability of an individual’s caffeine intake would be like. The proportion of coffee intake, 0-99, 100-199, 200-299, 300-399, and 400-499, in the population are approximately 20.231%, 19.903%, 19.871%, 20.000%, and 19.995%, respectively. A single individual is chosen at random from the population. List the sample space for this experiment. Assign probabilities for each of the simple events (ranges). What is the probability that the person chosen at random has either 0-99 or 200-299 mg of caffeine intake? The sample space will be the events/ranges that are given. Assuming each event has an equal probability to happen, we can assume that their number out of 100 will be their probability. Lastly, we can find the probability of events by adding their probabilities.

In terms of probability, we can find certain information that could be useful for understanding the demographic that our population consists of. For example, a group of individuals contains six people. Two of the six are to be randomly selected to be classified as cognitively healthy or unhealthy. If two of the people are unhealthy, find the probability that at least one of the two people checked is unhealthy. Find the probability that both are unhealthy. If four of the people are unhealthy, find the probabilities indicated from before. To approach this problem, it would be best to find the sample space of all possibilities, then add the probabilities based on the criteria given.

As the research in cognitive performance becomes more well known. More and more people are beginning to volunteer for research. Due to the influx of volunteers for the research, a raffle with 8000 tickets was handed, one per volunteer. There are only three positions needed to be filled. If four of the researchers were also given one ticket each, what is the probability that the four organizers will win all the tickets? Exactly two of the tickets? Exactly one of the tickets? None of the prizes? This problem can be solved via using the formula for combinations. Each combination changes based on the desired results.

Although our population consists of any individual older than a teenager, it is important to learn about how screen time has affected cognitive performance. For example, individuals are randomly selected from the population of 8000. Given that there are 31 different sleep amounts (refer to Figure 5). If the first two individuals picked have a screen time duration of 7 hours, what is the probability that the next three individuals will also have the same screen time? If the first three individuals have a screen time duration of 7 hours, what is the probability of the next two people having the same screen time? If the first four people have a screen time duration of 7 hours, what is the probability that the next person will also have the same screen time? This problem can be solved by using a mixture of combinations and conditional probability.

To further learn more about the ages of volunteers in our population, we can construct a problem that concerns a mixture of probability and independence of events. For example, If A, being the age between 18 to 19, and B, being the age between 20 to 21, are such that . Find the following: , , and . We can solve this problem by using our understanding of additive and multiplicative law of probability.

An interesting information we can learn from the data is to compare how cognitive performances differ depending on the gender. We can construct a problem to learn more about this. For example, male (and others) and female were observed to have varying cognitive performance scores. It shows that 60% of females had high cognitive scores, 50% of males and others had high cognitive scores. A group of 30 people, 20 female, and 10 males, were subjected to a test to check their cognitive performance. The response picked at random from the 20 had low scores. What is the probability that it was that of a male or other? This problem can be solved by using Baye’s theorem and Theorem of Total Probability.

A problem with the cognitive test was given to the volunteers. This test was one of the primary ways of analyzing cognitive performance. The task was to match three pictures of animals to the word identifying that animal. If a participant assigns the three words at random to the three pictures, find the probability distribution for Y, the number of correct matches. This problem can be solved using the probability distribution for a discrete random variable.

As a follow up from the previous experiment, another test was conducted with more pictures to be matched. In the following information that was gathered, a problem can be asked to find the expected and variance of the number of correct matches. Let Y, the number of correct matches, be a random variable p(y), the probability of it occurring, given in the accompanying table. Find .

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| y | 0 | 1 | 2 | 2 | 4 |
| P(y) | 0.2 | .2 | .3 | .2 | .1 |

In an experiment with the volunteers, coffee was studied to see any correlation with cognitive performance and caffeine intake. Two types of coffee were presented: formula A (with a much lower caffeine concentration), and formula B (with a higher caffeine concentration). Four participants were selected, each given three cups of coffee in random order. Two contains formula A and the other contains formula B. Each participant was asked which of the cups made them focus more. Suppose that the two formulas are equally performant. Let Y be the number of participants stating a preference for formula B. Find the probability distribution function for Y. What is the probability that at least three of the four participants will state a preference for formula B? Find the expected value of Y. Find the variance of Y. This problem can be solved using our knowledge of Binomial probability distribution.

Another factor that may play into a deteriorated cognitive performance is through higher levels of stress. Stress is known for its adverse effects on general health. Here, we can learn about how stress may affect cognitive performance. For example, of the population of participants, 60% have high stress levels (8+). If a group of randomly selected participants is asked, what is the probability that exactly five people must be interviewed to encounter the first participant who has a high stress level? At least five people? This problem can be solved by using Geometric probability distribution.

Alongside testing cognitive function, memory plays just as big of a role in keeping high cognition. During analysis, it was found that 25% of participants had a memory score from 400 to 500. If you were to randomly ask a participant, what is the probability that they would have more or less of a memory score on the first try? The second try? The third try? Given that you have a coworker, and the examination needed to be speed up, what is the probability that a total of four tries will be necessary for the both of you to find someone not having a 400-500 memory score? This problem can be solved using Negative Binomial probability distribution.

During the early phase of testing, data was recorded. At one point, ten participants were fully examined. Four have been found to be non-vegetarian. The researchers select five participant records. What is the probability that all five participants were vegetarian or vegan? This problem can be solved using Hypergeometric probability distribution.

While interviewing the volunteers, it was found that the amount of sleep a participants get has a Poisson distribution with an average of seven hours per day. If more than seven hours were slept in a day, the participant scores a higher cognitive performance. What is the probability that a randomly selected participant will not score a higher cognitive performance? This problem can be solved using Poisson probability distribution.

Amongst the 8000 participants, the average cognitive score was 58 with a standard deviation of 23. Using Tchebysheff’s theorem, find a lower bound for the number of participants from a 500-sample expected to have a cognitive score between 50 to 80. As the problem implies, this problem can be solved using Tchebysheff’s theorem.

One of the tests given to the volunteers was a challenge to open a box. To open a box, they must sort through multiple challenge questions to earn a key. There are only five keys to obtain. Each key earned and tested is thrown away. We want to model the problem where Y is the number of trials where the lock is opened as a probability function. We also want its corresponding distribution function. Finally, we would like to find the following probabilities: . This can be solved using knowledge regarding probabilities of continuous random variables.

Following the previous example, if Y has a density function:

We would like to find the mean and variance of Y. This is solved through the definitions of expected and variance values for continuous random variables.

Luckily, the company was able to procure an AI algorithm that can predict cognitive performance scores given the data that was available. The AI predicted scores are uniformly distributed over the interval of 70 to 80 points. What is the probability that the score exceeds 75 points if it is known that scores exceed 72 points? This can be solved by using the Uniform probability distribution.

It is known that caffeine intake has some form of relationship with cognitive performance. To further study this factor, we focus on a given model where a barista at a local store that many of the volunteers go to observe that during the mid-day hours there is an approximately exponential distribution with a mean 300 mg per coffee cup sold. We want to know what the probability of the demand for more caffeine will exceed 400 mg per coffee cup on any random day. In addition, what would be the amount of caffeine per cup should the barista maintain during any random day so that the demand will exceed the capacity is only .05? This problem can be solved using the Gamma probability distribution alongside the exponential distribution of a gamma function.

The volunteers were tested in several different ways. One way was to test their reaction times via abruptly announcing tasks to do, mainly to choose a testing site from two different options: A and B. The amount of time taken to choose between one or the other was recorded. Two volunteers were tested at the same time. We want to learn how to model the joint probability function, given that is the number of volunteers that went to site A, and is the number of volunteers who went to site B. Furthermore, we want to know what the value of is? This problem can be solved by finding the probabilities for each pair within the sample space and using the theorem for the join distribution function.

# Results

According to the constructed relative frequency histograms (found in the Figures section), we can see a diverse distribution of each category. In Figure 1, we can conclude that there is an almost even distribution of Men, Women, and others who volunteered for this dataset. This gives us confidence that derived information will be applicable for all kinds of individuals. Even more so, as Figure 4 shows us multiple participants across all age ranges from 18 to 59.

Some other notable figures to mention are Figures 2 to 8. These figures exhibit the distribution of other factors that may affect cognitive performance. Notably, with Figure 7 having a distinctive concentration of having a screen time of 9 to 11 hours. This may or may not have adverse effects on overall cognitive performance.

A graph of a graph

AI-generated content may be incorrect.

Figure 7: Screen Time Relative Frequency Histogram

To learn more about the dataset, we are required to calculate the central tendency values of the numerical data. According to Figure 13, we can see these values such as mean, median, mode, variance, and standard deviation.

A table with numbers and a few black text

AI-generated content may be incorrect.

Figure 13: Central Tendency Data of Numerical Data

This data shows that from the dataset, the average participant was about 38 and a half years old. While the most common age being 40. Sleep duration shows that the average amount of hours slept is about 7 hours, while the most common being 3 hours. Stress levels average around 6.5 while the most common being 3. Daily screen time averages about 6.5 hours per day while 7.7 hours per day being the most common. Caffeine Intake averages 249 mg per day, while 76 mg per day being the most common. Reaction time averages 400 ms while 260 ms being the most common. Test scores, specifically, Memory scores show that the average score was 69.6, while 57 being the most common. Cognitive scores are shown to have the average score being 58.2 and 100 being the most common. Lastly, an AI model’s average prediction for cognitive scores of each individual shows to be 58.1 whole the most common being 100.

Although Figure 8 does not illustrate an approximately normal (bell shaped) distribution, to answer the sleep deprivation problem it is still possible to use the empirical rule. Based on the empirical rule, one standard deviation would contain 68% of the measurements, two standard deviations would contain 95% of the measurements, and three standard deviations would contain 99.7% of the measurements. Therefore, we can calculate each standard deviation:

We can then find that the participants that have sleep deprivation between 4.00 to 10.02 hours is (4.00, 10.02) or one standard deviation, therefore 68% of the participants were sleep deprived. Similarly, sleep deprived participants between 0.99 to 13.03 hours is (0.99, 13.03), therefore 95% of participants are sleep deprived. For hours between 4.00 to 16.04 hours, we have 4.00 for the lower bound, while for the upper bound we have 16.04. This means that 81.5% of participants were sleep deprived. Finally, we can find the fraction of sleep deprived participants in the range of -2.02 to 16.04, which is three standard deviations, therefore 99.7% are sleep deprived. But since we are looking for those that are less than -2.02 or more than 16.04, we can perform the following:

This is possible since the entire distribution should be added to 100%, and we only desire those outside of 99.7%. Therefore, the fraction of sleep deprived participants with less than -2.02 or more than 16.04 hours of sleep is 0.003 or 0.3%.

Through set notation, we can group multiple characteristics of everyone. This can help in finding groups that may or may not fulfill certain conditions. To do so, we construct space S, which contains all the combinations of each characteristic.

Based on the given description, we can construct each set of notations that fulfill it. Therefore, A, containing no VGN will be:

Following a similar pattern, B containing a female will be:

Then we can also find C as:

Now that we have found A, B, and C, we can continue to create the sets for the following descriptions: A, B, C, A B, A B, A C, A C, B C, B C, and C .

To learn more about caffeine intake of our dataset population, it would be important to assign probabilities for each range we have found from the excel graphs. As shown in the following sample space, these constitute the ranges of how much caffeine were taken:

Based on the data found through the relative frequency histogram of caffeine intake, we can assign the distribution/probability of each simple event we have listed:

For example, if we randomly choose a volunteer and we wanted to know what the probability is for the volunteer to have a caffeine intake of 0-99 or 200-299, then based on Axiom 3 of probabilities of an event, we simply add the probability of each event as shown:

Screening volunteers are a crucial part of collecting data. In our given scenario, we want to learn more about the probabilities of finding cognitively healthy individuals given that some may not be healthy. To do so, we want to construct a sample space to understand each combination of the scenario given. Let us denote sample space s, with P# as a person/volunteer.

Given that two people are found to be unhealthy, we can assign to be the unhealthy ones. To find the probability of one or more being unhealthy, after selecting two, is the same as any of the events where appears. Therefore,

And both being unhealthy would be,

Now, given that four in total were found to be unhealthy, we want to know what the probabilities are, let us assume are unhealthy. Then,

To find the probabilities of the researchers being some of the volunteers, we can use combinations. We can find the total number of combinations in which the researchers win which are:

We also know the total number of combinations of winning the tickets which are:

With this information we can find the probability of each given scenario:

To learn about how screen time has affected the population in our dataset, we proposed probability questions regarding conditions. If we want to know the probability of the next three individuals with the same screen time, given that the first two had 7-9 hours of screen time we can use the definition of conditional probability. Based on the definition of conditional probability, we can conclude that:

Following the same pattern, we can solve the next scenario as show:

Finally, for the final scenario, we can solve as follows:

When learning about our dataset’s age ranges and occurrence, we proposed a problem concerning the additive and multiplicative law of probability. We want to know certain probabilities based on age. Here we can solve the probability of a randomly selected volunteer that can either be between 18 and 19 or 20 to 21 based on the additive law:

When looking for the probability of an individual not being aged between 18 to 19 and 20 to 21, we subtract from the total probability (1) due to DeMorgan’s Law:

The last scenario given follows a similar pattern:

When comparing cognitive performance between genders, we wanted to find the probability of males or others were the ones that scored low. Given the information, we can find the following probabilities based on conditional probabilities:

(MO – Male/Other, F – Female, H – High score, L – Low score)

With this information, we can find the probability of the low score being male or others using Bayes theorem:

To model the probability distribution of Y, the number of correct matches given the test, we would need to first construct the total number of possible outcomes:

This represents the number of ways the volunteer can choose their matches. With this we can assign the probabilities for Y as follows:

2 matches are ignored since it’s implied to get all matches,

Given that the probability of the number of correct matches was given, we can find the mean, variance, and standard deviation of a random variable. Mean is defined as:

During the test to find the effects of caffeine intake on the volunteers, we wanted to find the probability of three of the participants preferring formula B. Based on the information given we can construct the Binomial distribution for the given scenario as:

We can then find at least three preferring formula B by the following:

Then to find the expected and variance values, we do by:

When examining how much stress can affect an individual, a survey was performed to determine what the likelihood of finding a volunteer that has high stress. Here we do so by using the geometric probability distribution as follows, specifically for needing 5 individuals to interview:

Then to find the probability of having interviewed at least 5:

As noted, before, testing memory is just as important as stress. If we want to find the probability of a volunteer having a memory score from 400 to 500, we can model this through the negative binomial distribution. As shown in the following, we can find the probability of having success on the first try,

On the second try:

On the third try:

Having a coworker and needing only four tries:

To learn more about if diet types have any effect on cognitive performance, an experiment was conducted as mentioned before. We want to know the probability of five participants being vegetarian or vegan for further study. With the given information, we can solve this problem with hypergeometric distribution:

In the experiment of learning more about sleep, we are given the information that amongst the participants sleep had a Poisson distribution with an average of seven hours per day. Given that higher cognitive performance is due to more than seven hours of sleep, we want to know the probability that a randomly selected participant won’t have a higher cognitive performance. We know lambda is 4 (given by the problem), thus:

When analyzing the cognitive scores of the population, we wanted to find the number of participants that fell under a certain score range. Specifically, we wanted to know how many falls under 50-80. We restricted the population count to 500, but by doing so we can use Tchebysheff’s theorem to find a lower bound. In the experiment it gave information on mean and variance. Thus,

Based on the Tchebysheff’s theorem, we can find the value of k:

Now that we have k, we can find lower bound:

During the box test we want to model the problem with a probability function Y. Thus:

Given the information we found, we can find the distribution function as:

Therefore,

With this information we can find the following probabilities:

Following the previous problem, we now want to know the mean and variance based on the given density function. Mean is modeled as:

Then variance follows as:

When evaluating the AI model for accurate cognitive score predictions, it’s important to compare to the true values. Therefore, we would like to find the probability of a score exceeding 75 when it is known that scores exceed 72. To do so we need to find the probability of the given conditional probability:

With the given range, we can find the function for the interval:

Then, we find the numerator:

Then the denominator:

Therefore, the probability would be

Given the information about the store, we are given the gamma value. With this we can model the problem with a gamma probability distribution to find the probability of the demand exceeding 400 mg of caffeine. This is shown in the following:

Then to find the new capacity we would do the following:

We need to solve for t where the capacity is only 0.5:

During the reaction time test, we want to model the experiment as a joint probability function as well as finding the value of . To do so we need to construct the sample space:

With the sample space found, we can construct a table representing the distribution of and :

|  |  |  |  |
| --- | --- | --- | --- |
|  |  |  |  |
|  | 0 | 1 | 2 |
| 0 | 1/9 | 2/9 | 1/9 |
| 1 | 2/9 | 2/9 | 0 |
| 2 | 1/9 | 0 | 0 |

Based on the table, the value of is as follows:

# Discussion

Based on the results found from the various histograms constructed, we can learn a lot about the dataset we worked on. Briefly, we can see how the data is distributed amongst each category. This allowed us to create multiple types of experiments using information about the data. Although, there are some limitations to what we can learn from the data alone. The dataset itself does not provide extra information regarding how each data was collected, especially for each cognitive performance results. This is a key limitation because this will impact how much we can assume that a factor may affect these scores. But despite all this, we confidently used our visualized data for multiple tests to see how different factors did affect cognitive performance.

In terms of metadata, data about data, we learned about primarily numerical data’s central tendency values such as mean, median, and mode. This gave us many opportunities to create problems that require these values. Furthermore, it quickly gives us insight into some important details about each category such as the highest amount of caffeine intake, average screen time, and more. This information only helped us further in trying to understand how each category was distributed.

To understand the data even further, we even experimented on finding how much of the data falls under a certain interval. We did so through the empirical rule. We learned that for sleep deprivation specifically, almost 68% of the population in our dataset were sleep deprived. This is important because this could have possibly skewed the results of the cognitive performance data as well as the AI predicted scores. Although, it is important to note that the sleep duration analysis did not yield a normal distribution, so our conclusion may not be entirely accurate as some data may fall under or over the indicated interval.

In the following experiments, we did a lot of statistical analysis primarily regarding probabilities of certain events occurring. But to model the events at a smaller scale, we did so through set notation. We found multiple types of events regarding diet types. We learned how some certain categories may combine as well as not.

Finding probability for certain events was a crucial portion of our analysis. This allowed us to predict certain events or conclusions even before testing. One such example is through predicting that a certain individual from the population may have a certain caffein intake range. One example is if we wanted to find an individual that may have a caffeine intake range of 0-99 or 200-299, there would be 40.102% chance of doing so when randomly choosing a volunteer. Finding these probabilities can help us quickly determine any given scenario that we may want to consider.

This problem was further modified especially when looking into individuals that may have been considered as cognitively unhealthy. Finding the probability of individuals being unhealthy given the information of knowing some are unhealthy helped us learn how our dataset may contain those types of individuals.

We also learned about how to use combinations to predict certain events from happening. We did so use the raffle example. Through this example we learned what the probability is for certain events to occur, specifically the chances of winning an X number of tickets. This can be further modeled to other scenarios such as finding probability the number of unhealthy sleep times in a group.

When given a condition known to be true, we were able to find the probability of an event given that condition. This was done through a sleep experiment in which we found some information regarding the amount of sleep of the population. Using conditional probability, we learned how to predict the chances of an event occurring given what we know.

We implemented multiple experiments/problems that deal with the various categories of the dataset. This also allowed us to use multitudes of theorems and definitions regarding probability. Another example would be the experiment with age. We want to know the probability of certain age groups combined given that we define some age groups. For example, we found that the probability of finding an individual that is either aged between 19 to 19 or 20 to 21 was 9.24%.

When comparing the results of cognitive performance based on gender, we used Baye’s theorem and the theorem of total probability. This allowed us to be able to predict the possibility of a certain gender being the one to gain the result of a test. For example, given in the experiment, we found that the chances of a male having a low score from the 20 responses was 33%.

To learn more about the participants and their cognitive performances, many tests were performed. One test specifically analyzed their cognition through picture matchmaking. In this experiment we learned about the probability of each possible scenario for the test. If a participant scores 1 or none matches, then it was likely to happen 33% of the time. Otherwise, they would match everything correctly around 17% of the time. This helped us find the average and variance of scores. Similarly, we also found the expected, variance, and standard deviation values for the function modeling the correct matches.

During the experiment regarding caffeine intake and perceived benefits of two formulas, we learned how to predict the chances of any number of individuals preferring a certain formula. This can help in creating a safer yet still beneficial formula that contains a safe amount of caffeine for daily consumption. For example, in our experiment we found that a minimum of three or more judges would prefer the formula with higher caffeine concentration 11% of the time.

Learning about stress was especially important as it can affect anyone. Through our experiment we learned how to find the probability of finding an individual with high stress with X amount of tries. In our problem we learned that with five people analyzed, there is a 2.56% chance of finding someone with high stress afterwards.

With the memory score experiment, we learned the probability of finding individuals with a certain score given an X amount of tries. This was mainly done using negative binomial probability distribution. For example, we found that on the first try there is a 75% chance of finding someone with a memory score between 400 to 500. This is especially useful if we wanted to predict how often we may want to find new volunteers with a certain memory score.

If, for example, the research was altered, and a new population was provided. We may have wanted to predict the chances of a certain group of individuals having a specific die type. We can do this using hypergeometric distribution. In the example, we found the probability of a group of participants being vegetarian or vegan was 2.381%.

Given that we know an average has a Poisson distribution, we can find the probability of finding an individual with a certain characteristic. This becomes flexible in many ways if wanted to learn more about the dataset, since we have the averages for all the numerical data. This can help in predicting randomly selected individuals to have a certain feature. For example, in our problem we found that the probability of an individual to have a lower cognitive score was 59.871% of the time.

If we wanted to downscale the number of participants but kept a certain number of individuals with a specific range of cognitive scores, we were able to do so using Tchebysheff’s theorem. For example, we found that if we had 500 samples and wanted to know how many had 50 to 80 as scores, then about 40.8% would. This is useful if we want to have a certain percentage of scores within our population.

In another test, specifically the key box test, we wanted to know the probability of the participants opening the box with a key. This was done using continuous random variables. We simply assigned each possible event and their probabilities and found each given scenario as well as their probabilities of occurring. One example is that there is a 40% chance that a participant opens a box within 1 to 2 keys.

Following the previous problem, this was further expanded by finding the expected and variance value of the problem, modeled with a density function. Knowing the expected and variance values helps in setting expectations on what to expect during a test. This will allow for quick recognition if there are any outliers or faults within the test.

Given that we know if an interval has a uniform distribution, we can find the probability of a value. This is in the assumption that we also know that a lower value exists. This was done through uniform probability distribution in our cognitive score analysis. We learned that for example, given we know that the scores exceed 72 points, and we want to know the probability of it exceeding 75 points, the probability is 62.5%. This is useful if we want to compare the results of the AI predictions to real world results.

An additional analysis was performed concerning the amount of caffeine being taken from a local store. We wanted to learn more about the probability of exceeding the average caffeine amount, and how much caffeine to prepare if there is a restriction on the total amount to sell for a day. By using gamma distribution, we found that the probability of exceeding the average amount is . And that the new average should be about 300 mg of caffeine if a capacity of 0.5 was specified.

In a different test, primarily to analyze reaction times, we wanted to focus on the manners in which the participants were choosing the testing sites. By creating a joint distribution function, we learned the probability of each given scenario on how the participants may have chosen the testing site. We can discern the probabilities of certain combinations such as which is 33%, meaning it is the probability that either contestant chose to go to site A or B.

# Conclusion

Overall, through multiple experimentations using the dataset as a basis for information, we learned many things that we did not know before. Despite some limitations that the dataset inherently had, we were still able to demonstrate knowledge in statistical analysis via various problems involving probability. We learned that there are many factors that can affect human cognitive performance, which are apparent through the results we have uncovered. Many of which do align with our previous thoughts such as lifestyle and individual habits. But all in all, we learned how to tackle, dissect, and analyze a real-world dataset to learn more about the data itself. Finally, we were able to demonstrate knowledge in using various statistical methods to learn and explain about the data.

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# Figures

A graph of a number of people

AI-generated content may be incorrect.

Figure 1: Gender Relative Frequency Histogram

A screenshot of a graph

AI-generated content may be incorrect.

Figure 2: Exercise Frequency Relative Frequency Histogram

A graph of a diet type distribution

AI-generated content may be incorrect.

Figure 3: Diet Type Relative Frequency Histogram

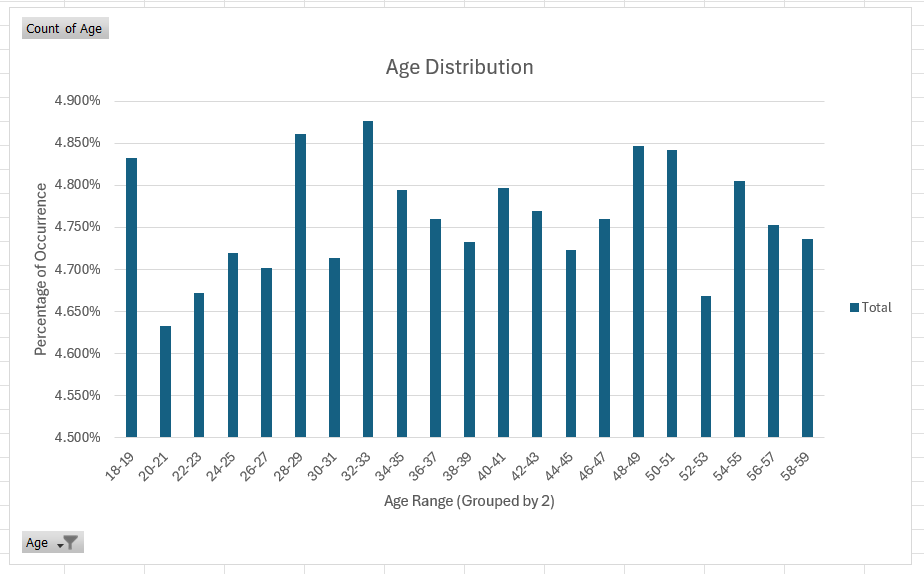


Figure 4: Age Relative Frequency Histogram

A graph of a sleep duration distribution

AI-generated content may be incorrect.

Figure 5: Sleep Duration Relative Frequency Histogram

A graph of a stress level distribution

AI-generated content may be incorrect.

Figure 6: Stress Level Relative Frequency Histogram

A graph of a graph

AI-generated content may be incorrect.

Figure 7: Screen Time Relative Frequency Histogram

A screenshot of a graph

AI-generated content may be incorrect.

Figure 8: Caffeine Intake Relative Frequency Histogram

A screenshot of a graph

AI-generated content may be incorrect.

Figure 9: Reaction Time Relative Frequency Histogram

A graph of a memory

AI-generated content may be incorrect.

Figure 10: memory Score Relative Frequency Histogram

A graph of a graph

AI-generated content may be incorrect.

Figure 11: Cognitive Score Relative Frequency Histogram

A graph of a bar chart

AI-generated content may be incorrect.

Figure 12: AI Prediction Relative Frequency Histogram

A table of numbers and a number

AI-generated content may be incorrect.

Figure 13: Central Tendency Data of Numerical Data