

Analyzing the Effects of Caloric and Macronutrient Consumption on Productivity: A Quantified Self Approach to Assess Work Patterns and Habits

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ABSTRACT

In this study, I examine the impact of caloric and macronutrient intake on personal productivity metrics, encapsulated by MacOS application engagement, iPhone application engagement, and frequency of unproductive application switches, during the three-hour period after a meal. As the quest for improved personal productivity intensifies in our modern society, understanding the link between dietary choices and cognitive performance takes on increasing relevance. Over a 26-day period, I systematically accumulated data on my food intake and productivity using self-tracking nutrition and productivity applications, such as MyFitnessPal and Timing App, respectively. I utilized statistical models to uncover the subtle interrelationships between food consumption and productivity. I found that a balanced macronutrient intake, particularly moderate to high protein and lower simple carbohydrate meals, was linked to greater productivity, while high caloric intake appeared to correlate negatively with productivity. However, my macronutrient intake did not necessarily impact my productivity, as did my meal timing and time of day. The time of day and my routine had a substantial edge on my productivity. These results suggest that dietary choices as well as one's own time-based routine can significantly affect personal productivity, paving the way for further investigation into optimized nutrition and influencing broader dietary and productivity strategies in various professional and personal settings.

Introduction

As the continual search for self-optimization in the realm of personal work productivity only increases, a relationship that remains comparatively unexplored is that of macronutrient intake and personal productivity. Macronutrients, such as carbohydrates, lipids (fats), and proteins, serve as the primary energy sources within the human body and are responsible for all the bodily functions and processes that allow us to operate accordingly (Venn, 2020). Therefore, one may assume a clear correlation exists between macronutrient intake and work processes. In this study, I aim to assess the possible correlations between these variables using self-tracking applications such as Timing App and MyFitnessPal.

The guiding research question is: "In the three-hour postprandial period, to what extent do variations in caloric and macronutrient intake influence productivity metrics, as quantified by MacOS application engagement, iPhone application engagement, and frequency of unproductive application switches?" The three-hour postprandial period, defined as the period directly after meal consumption, is of particular interest due to the immediate bodily responses and adjustments following a meal. Meal consumption at varying calorie levels could lead not only to an increase in glucose levels but also a consequential increase in insulin spikes, or, on the other hand, an increased level of satiety, regulating these spikes. These responses could have direct effects on cognition and productivity, contributing to the unique significance of this research.

Utilizing a Quantified Self approach, this study offers a rare opportunity to investigate these correlations in a real-life context, as opposed to the highly controlled conditions of traditional laboratory experiments. This shift in methodology may provide valuable insights into the nuances of the diet-productivity relationship as it unfolds in the complex landscape of our daily lives. However, with every different approach come particular limitations. Because this particular study revolves solely around my own personal eating and productivity habits, its findings may not be applicable universally (Gimpel et al., 2013). Additionally, given that I did not conduct this research in a highly controlled environment and instead opted to go about my routine regularly, various extraneous factors, which I will detail throughout this paper, could have potentially affected the results of this research.

Regardless, the findings of this research could have substantial implications beyond the academic realm. If a significant relationship between macronutrient intake and productivity is established, this could inform dietary guidelines for those seeking to optimize their work performance and acute cognitive function. Additionally, in the realm of the workplace, understanding the correlation between macronutrient intake and productivity could guide the development of healthier cafeteria menus or even the scheduling of work tasks relative to meal times. From a public health perspective, these findings might inform nutrition guidelines tailored not only toward physical health but cognitive performance and productivity as well. With the increasing popularity of self-tracking tools for health and productivity, insights from our study could assist in refining these tools to provide more personalized and effective dietary feedback. In essence, by exploring the understudied intersection of diet and productivity, this research holds the potential to shape policies, practices, and tools that better support our society's pursuit of health and productivity in an increasingly demanding world.

Thus, this study not only aims to fill a gap in the current scientific literature but also endeavors to provide practical knowledge that can directly impact individuals' daily lives and society's broader quest for enhanced productivity.

Background

Investigating productivity patterns in relation to dietary intake through a Quantified Self approach necessitates an understanding of two crucial concepts: the principles of the Quantified Self movement and the physiological process of dietary macronutrient metabolism in the body. Thus, this section of the paper aims to delve into these interlinked domains, exploring their intricacies to not only provide the necessary context but also to substantiate the research undertaken.

The Quantified Self Movement

Although the concept behind the Quantified Self has been around for decades, the term was officially coined in 2007 by *Wired Magazine* editors Gary Wolf and Kevin Kelly. This social movement is rooted in the idea that individuals can utilize self-tracking apps and devices to analyze their habits, aiming ultimately at self-improvement and habit enhancement. The advent of wearable technology and smartphone applications throughout the 2010s and into the 2020s has accelerated this movement, making self-tracking more accessible and easier than ever before. Thanks to devices such as the Apple Watch and Fitbit, the Quantified Self movement has gained significant traction. Looking ahead, market forecasts suggest that nearly 27% of healthcare diagnostics by volume will involve quantified-self solutions by 2028 (GlobeNewswire, 2023).

The underlying motive behind this movement is the belief that the more personal data we collect and analyze, the better we can understand and assess our tendencies. With rapid technological advances, individuals have unprecedented access to personal data, ranging from physical activities, such as steps taken and hours slept, to more internal metrics, such as heart rate and glucose levels.

Stephen Wolfram, founder and CEO of Wolfram Research, serves as a key example of the transformative potential of the Quantified Self approach. Wolfram has been meticulously gathering personal insights since the 1990s (Wolfram, 2012). This multi-decade-long data collection has revealed intriguing patterns that extend far beyond mere personal habits. A notable instance reflects the growth of Wolfram’s outgoing emails over the years, which mirrors the broader societal transition towards increased internet usage and online communication (See Figure 1). Wolfram’s detailed self-tracking practices serve as a methodological blueprint for the numerous discoveries individual data collection could lead to and the wider societal output these individual insights could generate.

Even on a more day-to-day scale, the importance of the Quantified Self movement lies in its potential to transform our approach to personal health and productivity. By equipping individuals with the tools and knowledge to monitor their own behaviors, it empowers them to make informed decisions, ultimately improving their health, well-being, and productivity.

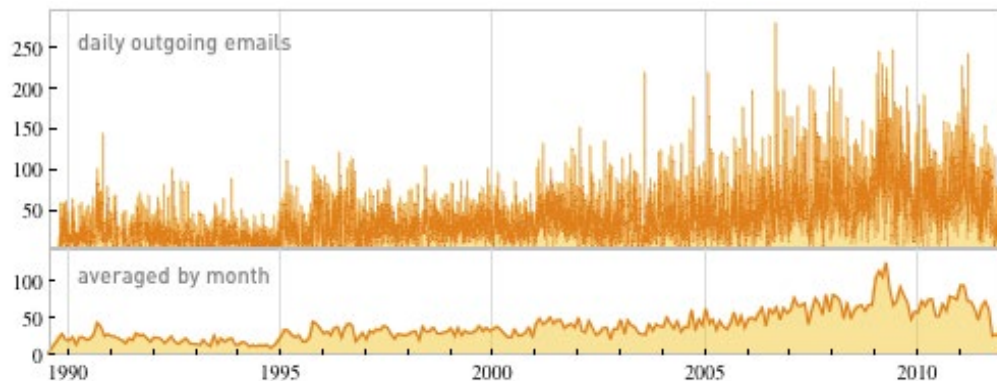


Figure 1. Diagram of Stephen Wolfram’s email frequency from 1990 to 2012. The graph is split into both daily outgoing emails and emails averaged by month, both reflecting an increase in emails sent (Wolfram, 2012).

Macronutrient Metabolism in the Human Body

The human body utilizes three primary macronutrients necessary for the proper execution of all its physiological functions. Although distinct in their structure and function, these three macronutrients—carbohydrates, fats, and protein—converge to support the body's overall health and contribute directly to the number of calories the body consumes.

Carbohydrates are the primary and most readily available energy source in the human diet. Primarily taking place in the small intestine, carbohydrates are broken down into their simplest form, glucose, and absorbed into the bloodstream. This process is facilitated by various enzymes, such as amylase, which is responsible for breaking down starches. An increase in blood glucose levels triggers the pancreas to release insulin, a hormone that enables glucose to be transported into cells to be used as energy (Norton et al., 2022). The speed and efficiency of this process vary depending on the type of carbohydrate consumed. Simple carbohydrates, such as those found in fruits, milk, and sugar, are easily digested and lead to a rapid spike in blood glucose. Conversely, complex carbohydrates, found in whole grains, legumes, and starchy vegetables, have a more complex molecular structure that takes longer to break down, leading to a slower, more sustained release of glucose into the bloodstream. This difference in glucose release plays a crucial role in energy levels, mood, and cognitive function, potentially influencing productivity patterns.

Contrary to generalized belief, proteins are not only responsible for the development and replenishment of bone and muscular tissue but also function as enzymes, hormones, and transporters, aiding in the regulation of our body. When introduced to the body, proteins are broken down into amino acids, a process that occurs primarily in the liver. After these proteins are broken down, the small intestine absorbs these amino acids and uses them to "code" for

new proteins. However, when glucose within the body is relatively depleted, these amino acids can also be converted into glucose in a process called gluconeogenesis. Additionally, some amino acids act as precursors to neurotransmitters, the chemical messengers of the brain. In the immediate postprandial period, an increase in circulating amino acids from protein digestion can influence the synthesis of these neurotransmitters, leading to increased cognitive performance (Suzuki et al., 2020). Prevalent in a variety of foods such as fish, meat, soy, and dairy products, protein not only has a sustained impact on our physical health but our cognitive capability as well.

Fat, the final macronutrient, serves primarily as storage for any excess glucose, which is kept as glycerin within these cells. Although they are often stigmatized, fats are still crucial in orchestrating the body's functions. Along with their energy storage purposes, fats help absorb nutrients, and some fats, especially omega-3 fatty acids, may actually improve cognitive ability (Swanson et al., 2012).

Collectively, these macronutrients make up the caloric content of food packaging, such as your favorite potato chips, or sports drink. A calorie, in dietary terms, is a unit of energy that the body uses to perform physical and metabolic functions. More specifically, the term refers to the energy required to raise the temperature of 1 kilogram of water by 1°C. When we talk about food, we refer to the potential energy that it contains, measured in kilocalories, which we commonly refer to as "calories." Both carbohydrates and proteins provide about 4 kilocalories per gram, while fats provide a hefty 9 kilocalories per gram. As all of these macronutrients represent different forms of energy, their caloric values are significant in determining metabolic sequence. Carbohydrates serve as the simplest energy source and the easiest to utilize, hence their low caloric content. Once the body is depleted of carbohydrates, it resorts to a more energy-dense macronutrient in fats, and finally, if the body becomes depleted of fats, which insinuates the body is in a state of starvation, it resorts to protein as an energy source.

Altogether, the caloric and macronutrient content in meals may have a significant impact on one's productivity, not only through the body's absorption of glucose but additionally through the non-energy related processes that influence the cognitive function of the brain.

Related Works

The next section of the paper will aim to specifically contextualize past research that acts as the framework for the current research.

The potential influence of macronutrient intake on personal productivity remains a relatively uncharted area of study, despite the fundamental role of macronutrients in human energy processes (Venn, 2020). The study by Bernard J. Venn suggested that the interplay of an individual's genetic makeup and microbiota features with specific macronutrient intakes or dietary patterns can explain individualized responses to macronutrients and food patterns. This underscores the complexity of nutrition and its effects, which must be taken into account when examining its impact on productivity.

The potential impact of macronutrients on cognitive function and productivity opens the opportunity to investigate what this impact may look like and how it may affect one's own productivity patterns in the three-hour postprandial period. Studies have shown that inadequate nutrition, characterized by high levels of saturated fats, simple sugars, and imbalanced protein intake, can induce oxidative stress and inflammation, leading to negative cognitive and structural outcomes and increasing the risk of unhealthy brain aging (Muth & Park, 2021). During the postprandial period, glucose and insulin production have a significant impact on acute cognitive function, a direct product of dietary macronutrient consumption (See Figure 2).

Furthermore, a past study by Nilsson et al. conducted on young adults has illustrated the variance in blood glucose levels within the four-hour postprandial period (See Figure 3). As depicted in the graph, there is a rapid energy increase at about the 45-minute mark. This observation could be applicable in my study, such that I could expect to see a productivity spurt in my own work tendencies at around the 45-minute mark, followed by a subsequent decline. Foods that induce a low but sustained blood glucose profile, such as wheat bread enriched with guar gum, have been

shown to enhance cognitive functions in the postprandial period, emphasizing the potential benefits of considering the glycemic impact of our diets on cognitive function and productivity (Nilsson et al., 2012).

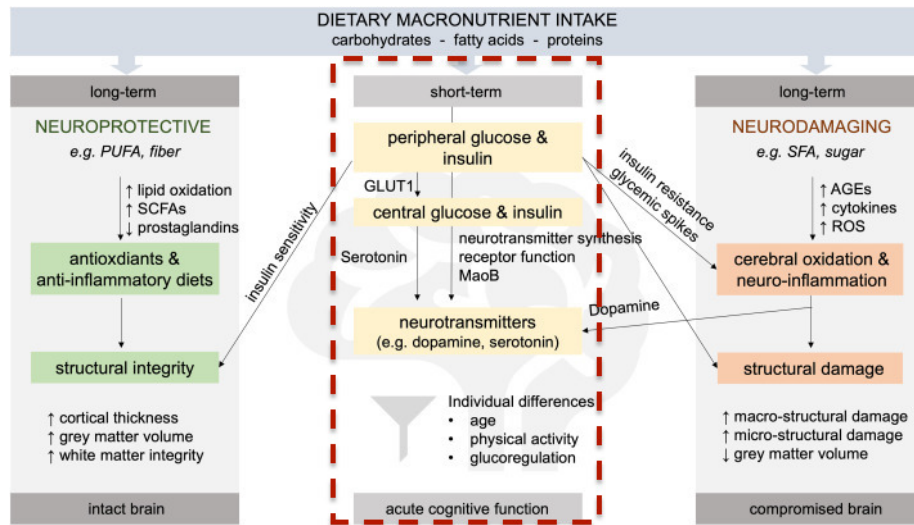


Figure 2. Short-term effects of dietary macronutrient intake. This process describes the decomposition of glucose when entering the human body and being converted into neurotransmitters through neurotransmitter synthesis (Muth & Park, 2021).

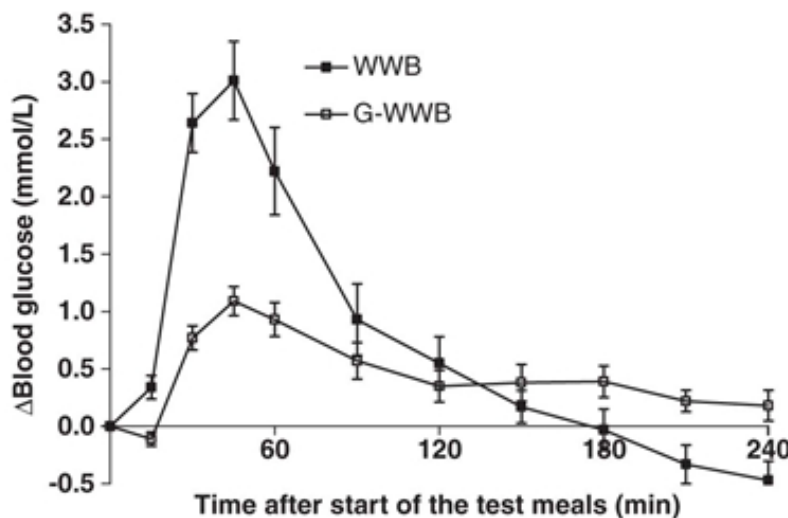


Figure 3. Blood glucose levels in the four-hour postprandial period. This graph depicts the spike of blood glucose at around the 45–60 minute mark after meal consumption. This relation may forecast a sudden spike in productivity, followed by a gradual decrease (Nilsson et al., 2012).

Though these studies provide valuable insights into the impact of macronutrient intake on cognitive function and postprandial glycemic response, they do not directly address productivity metrics that incorporate more plausible scenarios for us humans, such as application engagement on mobile and computer devices. This problem represents a crucial gap in the research that this study aims to address, considering the potential implications of diet on productivity in various contexts.

Data Collection and Methodology

This research employed a combination of self-quantification tools and software applications to collect and analyze data related to macronutrient intake, cognitive function, and productivity. Throughout the study, I used MyFitnessPal and Timing App. Additionally, I briefly considered other applications such as RescueTime and RealizD but ultimately excluded them as productivity and screen-time tracking options.

Failed Methodologies: RescueTime and RealizD

Initially, the study considered incorporating RescueTime and RealizD as tools for productivity and screen-time tracking. However, after careful evaluation, I determined that these tools were not suitable for the specific research objectives and I subsequently excluded them from the methodology.

RescueTime is a productivity tracking tool that automatically monitors and categorizes computer and digital device usage for both MacOS and Windows devices. It provides users with insights into their time spent on applications, websites, and tasks, helping them understand and optimize their productivity. RescueTime additionally includes two convenient features: application classification and application shifts. Applications can be classified as "Focus Work" and "Other Work," both of which are considered productive, as well as "Personal Activities," which are considered unproductive (see the blue outline in Figure 4). Furthermore, whenever RescueTime begins tracking a new application, the number of shifts on that application increases by one (see the red outline in Figure 4). This feature may be helpful when tracking how many times I switch between productive and unproductive applications.

RescueTime eventually became impractical due to its time-based data collection method. Data was collected hourly, meaning that any application used within an hour would be displayed as starting at the beginning of that hour (see the green outline in Figure 4). This limitation made it challenging to precisely track and analyze application usage within shorter timeframes, compromising the accuracy and granularity required for the research objectives. Originally, I decided to begin all my productive activities at the start of each hour in order to combat this issue. However, upon realizing that this approach contradicted the aim of full automation that the application, RescueTime, was intended to serve, I deemed the application unsuitable for the specific requirements of this study.

	interval	display name	work type label	duration seconds	time span	shifts
733	2023-05-30T12:00:00-07:00	chat.openai.com	Focus Work	769	12m 49s	2
734	2023-05-30T12:00:00-07:00	spotify	Other Work	232	3m 52s	3
735	2023-05-30T12:00:00-07:00	timing	Other Work	108	1m 48s	3
736	2023-05-30T12:00:00-07:00	youtube.com	Other Work	2	2s	0
737	2023-05-30T13:00:00-07:00	colab.research.google.com	Focus Work	704	11m 44s	0
738	2023-05-30T13:00:00-07:00	Google Spreadsheets	Focus Work	66	1m 6s	1
739	2023-05-30T13:00:00-07:00	netflix.com	Personal	37	37s	1
740	2023-05-30T13:00:00-07:00	pypi.org	Focus Work	30	30s	0

Figure 4. Sample set of RescueTime data frame with appropriate values outlined.

RealizD is a screen-time monitoring application available for both iOS and Android devices. This tool automatically logs and categorizes the time spent on different apps, providing users with valuable insights into their smartphone usage habits. RealizD offers a multitude of features, including total device usage, individual app usage, number of pickups, and continuous usage periods. Exportable data includes session start and end times as well as duration for iPhone pick-up (See Figure 5). However, RealizD presents some limitations that hinder its effectiveness for accurate time tracking.

	session start	session end	duration(seconds)
0	2023-06-02 22:39:25	2023-06-02 22:49:49	624
1	2023-06-02 22:25:49	2023-06-02 22:31:46	357
2	2023-06-02 22:24:52	2023-06-02 22:25:00	8
3	2023-06-02 22:11:10	2023-06-02 22:24:50	820
4	2023-06-02 22:10:12	2023-06-02 22:10:52	40
5	2023-06-02 22:06:24	2023-06-02 22:10:04	220
6	2023-06-02 22:06:03	2023-06-02 22:06:10	7

Figure 5. Sample set of RealizD data frame.

Despite its comprehensive feature set, RealizD doesn't sync with Apple's Screen Time, which often leads to inaccurate results. Furthermore, the application must be open in the background at all times to correctly log screen usage. This requirement makes it vulnerable to the device's power-saving settings, such as low power mode, which disables background app refreshes and thereby disrupts RealizD's tracking ability. These constraints hindered RealizD's practicality for this study, drastically underestimating real screen-time data, as the aim was to provide a reliable, automated solution for monitoring productivity. While RealizD has notable features that may aid in general time management, it was deemed unsuitable for the specific requirements of this research due to these setbacks.

Dietary Intake Tracking with MyFitnessPal

MyFitnessPal is a nutrition-focused application accessible on iOS and Android devices, serving as a vital tool in this research due to its ability to track and catalog dietary intake, thus providing comprehensive insights into a user's nutritional habits. A distinctive feature of MyFitnessPal is its expansive food database, which houses over 14 million foods, each of which comes with a detailed nutritional breakdown. This enables users to log their intake of proteins, carbohydrates, fats, and even micronutrients such as vitamins and minerals. This granular level of information about nutritional content is beneficial for understanding how specific dietary components may influence energy levels and cognitive function. Users can add this dietary data via a manual food search, by scanning a barcode on packaged food products, or by entering recipes and serving sizes for homemade meals. Each of these methods contributes to the accuracy and comprehensiveness of the dietary data collected. Furthermore, MyFitnessPal provides the ability to categorize logged foods into separate meals—breakfast, lunch, dinner, and snacks (See Figure 6). This feature enriches the dataset, enabling a nuanced examination of how dietary patterns correlate with macronutrient intake and productivity during different periods of the day (See Figures 7 and 8). Thus, through its extensive features and detailed food database, MyFitnessPal forms a robust platform for investigating the interplay between diet and productivity.

While the expansive user-contributed food database is a notable feature, it can also result in potential inaccuracies due to variability in nutrient values for identical food items. To address this concern, this study prioritized using verified food entries within the app to maintain data accuracy. Additionally, the premium version of the app, which allows for the logging of specific meal times, imposes a restriction of five-minute intervals. This granularity could introduce minor inaccuracies when tracking precise meal times, particularly when conducting an analysis correlating productivity with exact meal times. Finally, as with any manual-tracking app, tracking can become tedious over long periods of time. Regardless, MyFitnessPal's extensive features and comprehensive food database make it a desirable tool for investigating the intricate dynamics between diet and productivity.

Dinner	1,530
Net Carbs 148g · Fat 78g · Protein 40g	
6:40 PM	
Cheesy Gordita Crunch- No Beef, Add Beans	480
Taco Bell, 1 Cheesy Gordita Crunch	
Cheesy Fiesta Potato Bowl	240
Taco Bell, 1 bowl	
Spicy Potato Soft Taco	240
Taco Bell, 1 Taco	
Fiesta Veggie Burrito	570
Taco Bell, 1 Burrito	
ADD FOOD	...

Figure 6. Sample high-calorie meal at Taco Bell. Macronutrients are displayed above the menu items and calories are depicted in the leftmost column.

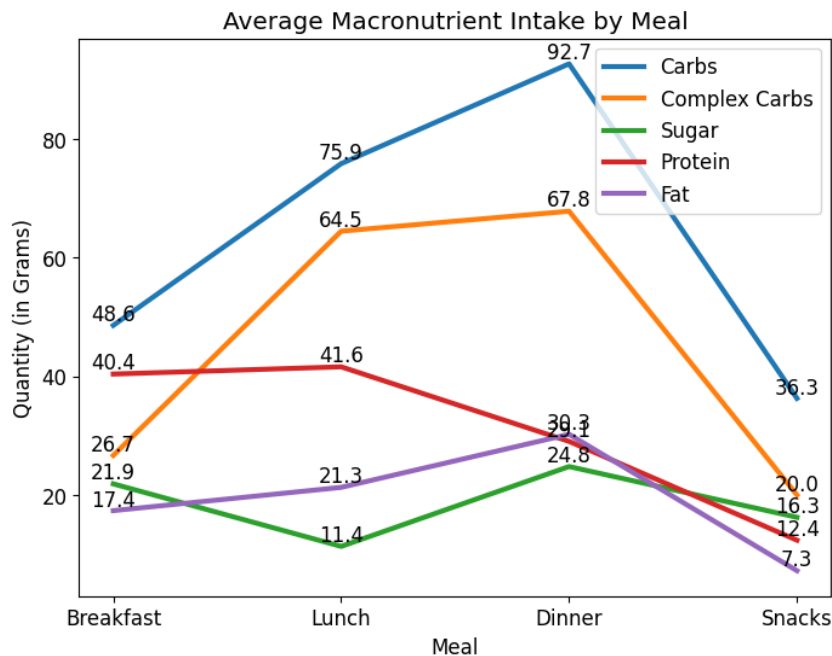


Figure 7. Comprehensive view of meals on mean values of macronutrient intake. Carbohydrates are additionally broken down into complex carbs and sugar.

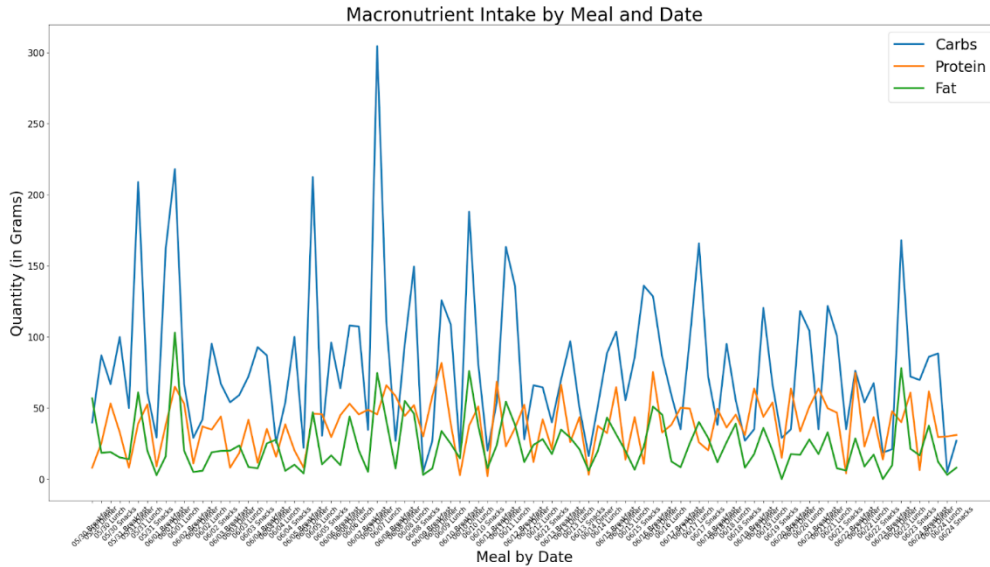


Figure 8. Comprehensive view of meals by date on macronutrient intake throughout the 26-day testing period.

Productivity Tracking with Timing App

Timing App, exclusive to Apple devices, is a central part of this research due to its robust time-tracking and productivity analysis capabilities. This application is designed to automatically monitor and categorize a user's activities on the computer, capturing a granular record of digital behavior. Its strength lies in the ability to record time spent across diverse activities, including applications, websites, documents, and tasks, as well as precisely document when these activities begin and end, to the very second. Furthermore, Timing App provides an intuitive timeline visualization of these tracked activities, arranged chronologically, offering a comprehensive depiction of a user's productivity journey throughout the day (See Figure 9). Additionally, another visualization Timing App provides is an application usage breakdown (See Figure 10). These visualizations can be instrumental in identifying productivity patterns and periods of high or low focus.

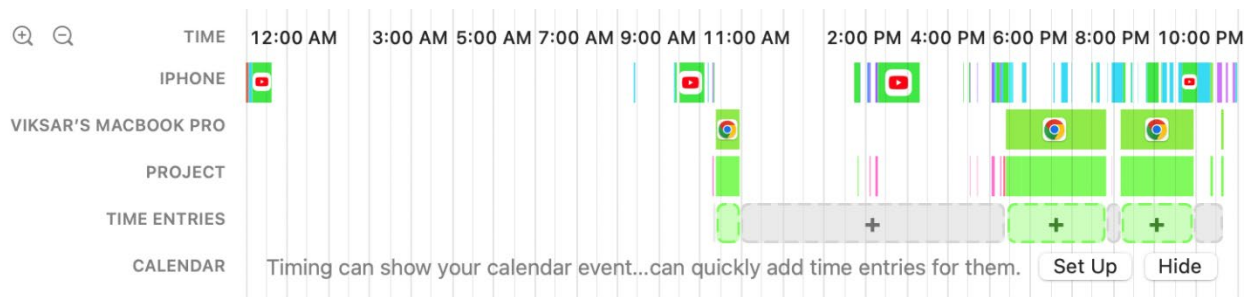


Figure 9. Visual timeline of application usage provided by Timing App.

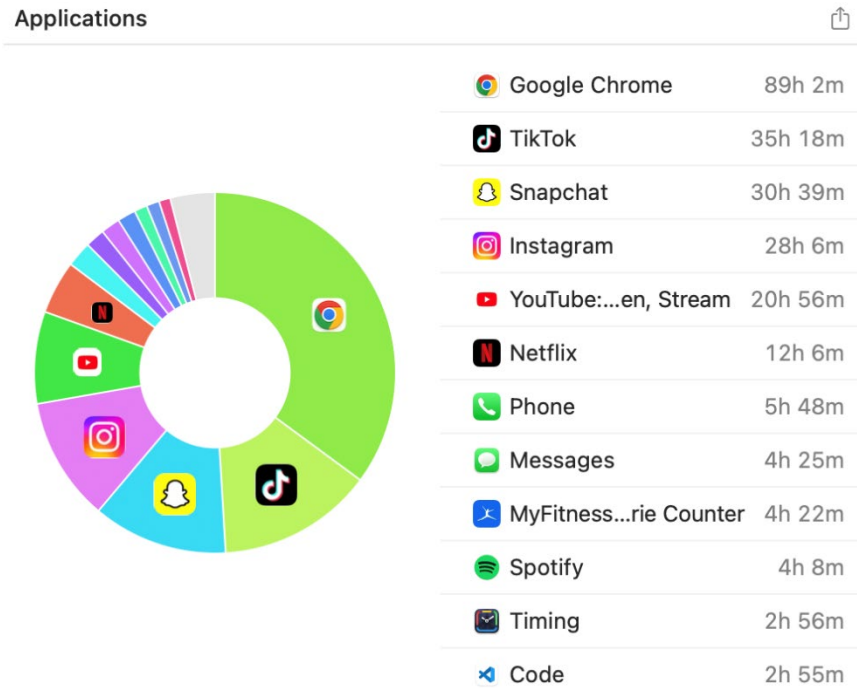


Figure 10. Pie chart by Timing App corresponding to total app usage across 26-day study.

Timing App doesn't have many downsides, aside from the fact that it is only available for Apple devices. Exclusively tailored for MacOS, it could be a potential hurdle for researchers or participants who operate on different systems. This restriction is what led me to use RescueTime initially, but upon recognizing that Timing App would be much more effective for this research, I stopped using my Windows device completely. Despite this limitation, the Timing App stands out with its cutting-edge automatic tracking technology, its customizable productivity categories, and its succinct, visual overviews of user productivity. Incorporating the Timing App into this study's methodology is anticipated to shed valuable light on the interplay between dietary patterns, cognitive function, and productivity.

Data Integration and Issues

For the analysis of the collected data, I leveraged Google Colab's computational environment to import, process, and analyze the datasets using Pandas, a powerful data manipulation library in Python. The raw data was exported from both MyFitnessPal and Timing App as CSV files, providing a common format for data integration. The initial step in data integration was to clean both datasets by dropping irrelevant or zero-like columns. For instance, in the MyFitnessPal dataset, I deemed columns such as "Vitamin A" and "Cholesterol" unnecessary for this study. Similarly, I excluded columns like "Notes" and "ID" from the Timing App dataset, as they did not contribute to the greater essence of this dataset—to assess productivity patterns.

One of the challenges of data integration was handling data columns with different formats. Specifically, the MyFitnessPal dataset had separate date and time columns in string format, whereas the Timing App dataset had a combined date and time column in DateTime format. To harmonize the datasets, I transformed the date and time data into a unified format across both datasets.

Another challenge was the classification of applications as productive or unproductive, a task that was performed manually (See Figure 11). This process could introduce some inaccuracies, given the dual nature of some applications. For instance, YouTube could be used for both productive research and unproductive leisure activities, perhaps when watching coding tutorials or cute cat videos. Nevertheless, an effort was made to minimize this potential bias by basing the classification on the dominant use case of each application. I made sure to only use Google Chrome,

an application I spent most of my online time on, for productive activities such as Google Colab and reading Scholarly articles.

App Name	Category	App Name	Category
Amazon Shopping	unproductive	Microsoft PowerPoint	productive
App Store	productive	Musi - Simple Music Streaming	productive
Apple Health	productive	MyFitnessPal: Calorie Counter	productive
Archive Utility	productive	Netflix	unproductive
Camera	unproductive	Phone	unproductive
Canvas Student	productive	Photos	unproductive
Captive Network Assistant	productive	PyCharm	productive
Clock	unproductive	RealizD - Screen Time Tracker	productive
Code	productive	ReportPanic	unproductive
Dictionary	productive	Safari	unproductive
FaceApp: Perfect Face Editor	unproductive	Slack	productive
Facetime	unproductive	Snapchat	unproductive
Finder	productive	Spotify	unproductive
Gmail - Email by Google	productive	System Preferences	productive
Google Calendar: Get Organized	productive	Taco Bell Fast Food & Delivery	unproductive
Google Chat	unproductive	Terminal	productive
Google Chrome	productive	Timing	productive
Google Docs	productive	Timing Tracker	productive
Google Maps	productive	TikTok	unproductive
Google Meet (original)	productive	Tablecruncher	productive
Google Sheets	productive	Weather	unproductive
Instagram	unproductive	YouTube	unproductive
Lock Screen Editor	unproductive	YouTube: Watch, Listen, Stream	unproductive
Messages	unproductive	zoom.us	productive

Figure 11. Classification of all applications across 26-day study as productive or unproductive.

Finally, I could not guarantee that the dietary intake data entered in MyFitnessPal was an exact reproduction of what actually went into my body, however many times I used a food scale to minimize inconsistencies. Although this might introduce some inaccuracies in the nutrient calculations, this issue was mitigated by prioritizing verified food entries and taking care to estimate quantities as accurately as possible. Additionally, I wanted to evaluate the difference in productivity output between simple carbohydrates (sugar) and complex carbohydrates (fiber and starch). However, only sugar and fiber existed as columns when MyFitnessPal data was exported, so I had to manually calculate the total starch in my meals by subtracting fiber and sugar from the total amount of carbohydrates and, with this value, adding the amount of fiber to the amount of starch to get the total amount of complex carbohydrates.

The ultimate goal was to integrate both cleaned datasets into a comprehensive one, mapping macronutrient and calorie intake for each meal against the corresponding productivity and unproductivity levels over a 3-hour span following each meal (see the red outline in Figure 11). This integrated dataset also included a metric for unproductive switches, signifying the number of times I switched from a productive to an unproductive application in the same time frame (see the blue outline in Figure 12). Creating temporary datasets was also a necessary strategy for handling this complex data manipulation process. These temporary datasets were used to generate specific visualizations that existed solely within the loops generating these graphics. To assess and visualize the relationship between diet and productivity, a combination of linear regression graphs and heatmaps was employed. I used scatter plots with a line of best fit (regplot) to identify potential correlations between macronutrient intake and productivity levels. Heatmaps provided a visual representation of productivity, unproductivity, and meal times, enabling a more intuitive understanding of patterns and trends. A subplot was also created featuring a pie chart of macronutrient consumption and a cumulative line graph of productive and unproductive time over the 180-minute period (See Figure 13). All of these visualizations will be further delved into within the "Results" portion of this paper.

Meal ID	Meal Date	Meal Start Time	Meal Type	Meal Calories	Meal Carbs	Meal Complex Carbs	Meal Sugar	Meal Protein	Meal Fat	Productive Time	Unproductive Time	Unproductive Switches
0	2023-05-30	00:00:00	Breakfast	298.4	0.0	0.0	0.0	0.0	33.8	0:00:00	0:28:35	0
1	2023-05-30	10:45:00	Breakfast	370.0	39.8	36.8	3.0	8.0	23.0	2:07:01	2:00:37	42
2	2023-05-30	13:25:00	Lunch	638.2	66.8	58.0	8.8	53.1	19.0	1:25:39	2:00:16	22
3	2023-05-30	21:15:00	Dinner	580.0	87.0	65.4	21.6	25.2	18.5	0:32:35	0:54:29	17
4	2023-05-30	15:45:00	Snacks	462.1	85.9	70.1	15.8	16.9	7.2	2:48:42	1:33:57	39
...
109	2023-06-23	07:40:00	Snacks	229.0	57.2	45.8	11.4	3.8	11.7	0:15:15	0:57:59	7
110	2023-06-24	11:15:00	Breakfast	932.5	86.0	64.1	21.9	61.7	37.6	0:42:59	1:20:36	4
111	2023-06-24	13:20:00	Lunch	160.0	5.0	4.0	1.0	30.0	3.0	1:15:09	1:20:43	10
112	2023-06-24	21:45:00	Dinner	573.3	88.4	55.0	33.4	29.6	12.2	0:24:42	0:00:00	0
113	2023-06-24	17:40:00	Snacks	300.0	27.0	18.0	9.0	31.0	8.0	1:26:14	1:59:14	9

Figure 12. Sample of nutritional intake on productivity with appropriate values outlined.

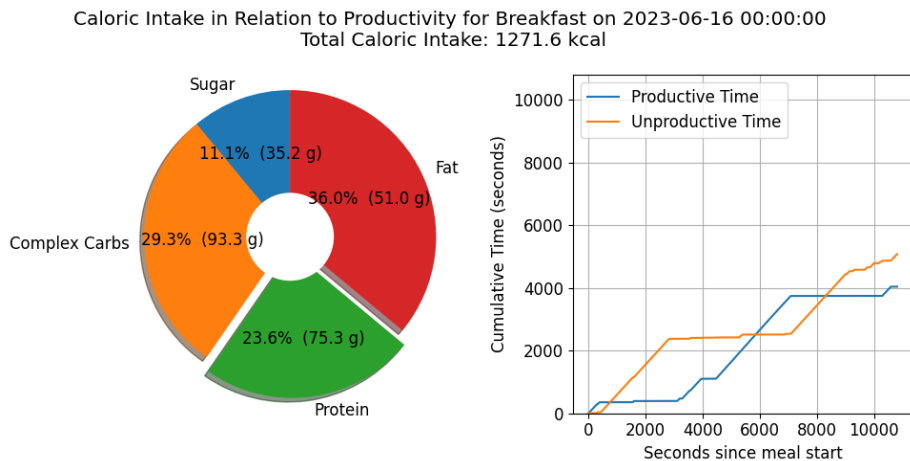


Figure 13. Plot containing pie chart of macronutrient intake (left) and line graph depicting productive and unproductive time (right) through the three-hour (10800-second) postprandial period.

Overall, this rigorous data integration and analysis process provided a comprehensive view of the intricate dynamics between dietary intake, cognitive function, and productivity. Despite the potential limitations and complexities, the methodology used was designed to ensure the highest possible level of accuracy and reliability.

Results

The main aim of this research was to explore the association between the intake of various macronutrients and productivity levels within a three-hour timeframe after a meal. The data gathered on 108 meals suggests a negative correlation between simple carbohydrate intake and cognitive performance that was two times more pronounced, and thus potentially detrimental, than with complex carbohydrate consumption. Additionally, my fat intake was by far the most expressive of a solid correlation with my productivity, as it rapidly decreased my work habits with every new gram I consumed. Notably, protein was the only macronutrient that appeared to enhance productivity as its intake increased.

Regarding significance scores, which I used in this section to assess the correlations I found, typically a score of 0.05 or less is considered statistically significant, suggesting that the observed results are highly unlikely to have occurred by chance alone. However, due to my relatively small sample size, significance scores lower than 0.05 were hard to come by. Therefore, with every significance score I mention keep in mind that with a larger dataset, these values could be lowered.

Effects of Caloric and Macronutrient Intake on Productivity

In an intriguing exploration of the role of caloric intake in productivity, my study uncovered a number of illuminating findings. Notably, dinner proved to be the most calorific meal, with an average of 867.48 calories, followed by lunch and breakfast at 693.45 and 535.45 calories, respectively, while snacks sat at the lower end of the scale with 255.85 calories. An outlier in the data was a single meal on June 1st, 2023, where the caloric intake surged to an impressive 3668.2 calories of pure Taco Bell, significantly beyond any meal type's average.

Despite initial assumptions, the correlation between caloric intake and productivity levels—both productive and unproductive—was relatively weak, with significance scores of 0.4231 and 0.2137, respectively, indicating that the number of calories consumed may not be a substantial factor in productivity. This was further corroborated by a graph plotting caloric intake against productive time, which demonstrated a negative slope of -0.875, suggesting that higher caloric intake could potentially be associated with lower productivity (See Figure 14). While this analysis provides some insight into the complex relationship between diet and productivity, it also highlights the need for further investigation, particularly with regard to the type and timing of caloric intake and controlling for external productivity influencers.

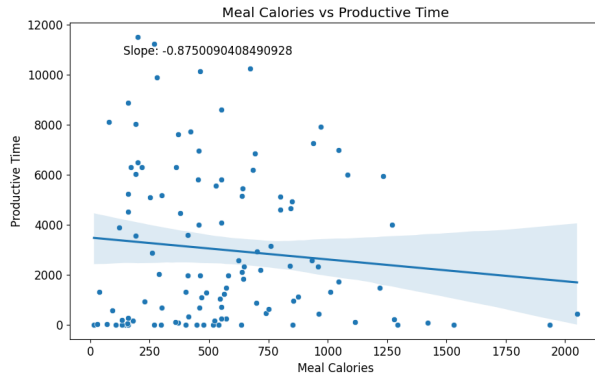


Figure 14. Caloric intake on my productivity.

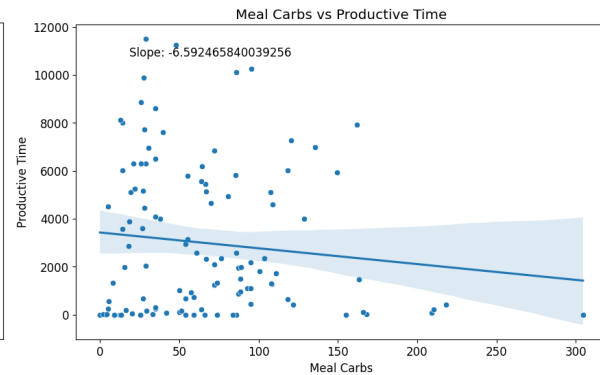


Figure 15. Carbohydrate intake on my productivity.

The impact of carbohydrate intake on productivity yielded mixed insights. Breaking down carbohydrates into total, sugar, and complex types, the data I collected suggested that dinner had the highest total carbohydrate and complex carbohydrate consumption, with averages of 111.09 grams and 81.55 grams, respectively. Lunch followed with an average total carbohydrate consumption of 79.47 grams and complex carbohydrates at 67.40 grams. Breakfast had total and complex carbohydrate averages of 52.00 grams and 28.71 grams, while snacks held the least with 36.16 grams and 20.35 grams, respectively. Sugar consumption was highest during breakfast, averaging 23.29 grams, closely followed by dinner at 29.54 grams, with lunch and snacks lower at 12.08 grams and 15.82 grams, respectively. Significant outliers included a meal on June 7th, 2023, that boasted an extraordinary total carbohydrate and sugar intake of 450.1 grams and 176.8 grams, and another meal on June 1st, 2023, when I consumed 361.0 grams of complex carbohydrates.

However, the correlations between total carbohydrates, sugars, complex carbohydrates, and productivity were weak, with significance scores for productive time at 0.4573 for total carbs and undefined for both sugar and complex carbohydrates. The unproductive time significance score for total carbs was 0.1625, with sugar and complex carbs undefined again. The slopes of -6.592, -14.681, and -7.307 for total carbohydrates, sugar, and complex carbohydrates, respectively, indicate that for each gram of intake, productive time decreases by the respective amount in seconds (See Figures 15, 16, and 17). This relationship does not necessarily imply causation, but it does suggest a correlation that might be worthy of further investigation. Particularly, the data gathered suggests a negative correlation

between simple carbohydrate intake and cognitive performance that was two times more pronounced than with complex carbohydrate consumption. This finding underlines the importance of a detailed and nuanced understanding of the role and impact of carbohydrate types on daily productivity.

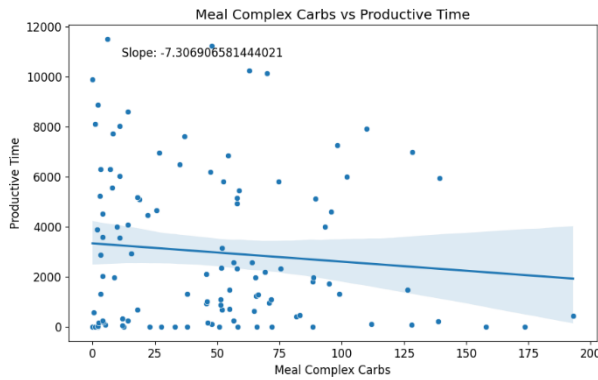


Figure 16. Complex carb intake on my productivity.

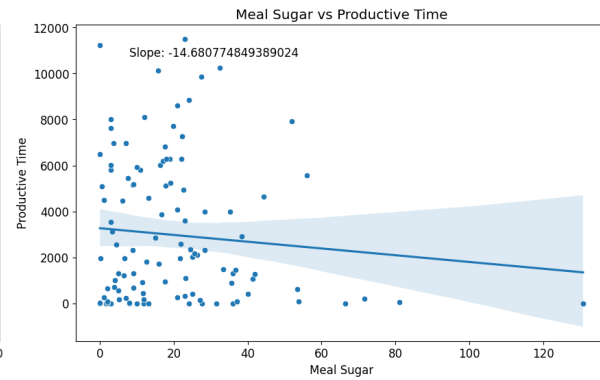


Figure 17. Sugar intake on my productivity.

Exploring the realm of dietary fats, I found some compelling patterns. Looking at the average fat intake for each meal type, I observed that dinner had the highest intake with about 35.20 grams of fat. This was followed by lunch, which averaged 22.74 grams, with breakfast slightly lower at 17.40 grams. As expected, snacks recorded the lowest fat intake, averaging around 7.57 grams, which is probably reflective of the lighter nature of these meals. There was one day that notably stood out: June 1st, 2023, when my fat intake shot up to an impressive 139 grams due to the consumption of fatty foods from Taco Bell.

When I delved deeper to understand the correlation between fat intake and productivity, I was struck by the noticeably lower significance scores compared to those seen for other macronutrients. For productive and unproductive time, the scores were 0.2352 and 0.1417, respectively. This suggests a potentially stronger statistical link between fat intake and my productivity levels compared to protein, carbohydrates, and sugars. Interestingly, the slope of the graph when plotting fat intake against productive time was -40.98, quite a substantial number following the negative sign when compared to other nutrients (See Figure 18). This indicates that for every additional gram of fat consumed, my productive time seemed to decrease by around 41 seconds. This correlation could be influenced by a multitude of factors, and it needs a more detailed investigation. Even with this potential negative correlation, the findings still highlight the intricate relationship between diet and productivity, underscoring that a balanced and varied intake may be the key to optimizing cognitive performance.

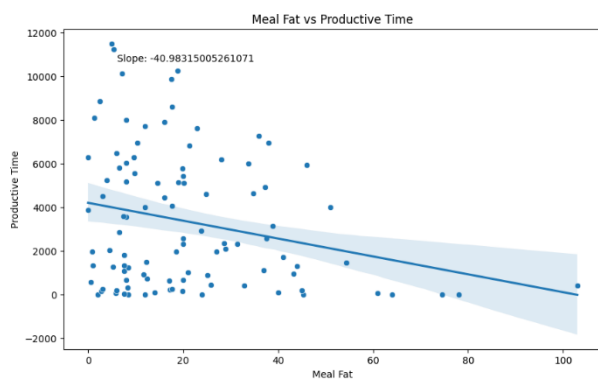


Figure 18. Fat intake on my productivity.

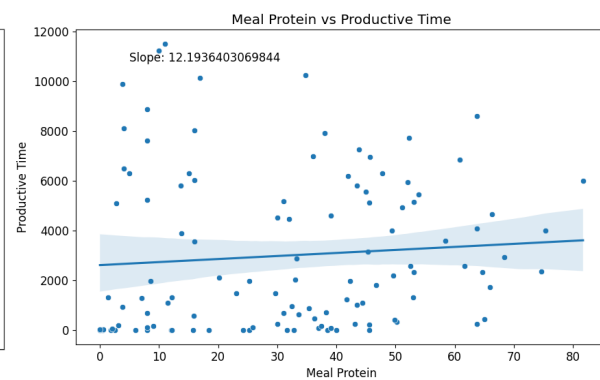


Figure 19. Protein intake on my productivity.

In the realm of protein consumption, the data presents an interesting trend. Both breakfast and lunch boasted similar average protein intakes, coming in at 42.55 grams and 43.33 grams, respectively. On most days, I consume a protein shake for both breakfast and lunch, therefore boosting these values. Dinner, however, reflected a slightly lower protein consumption at an average of 33.53 grams, indicating a potential tendency to favor other macronutrients during evening meals. My protein intake during snack times was considerably less, averaging only 13.03 grams, due to the already low caloric intake for this meal. An outlier day in terms of protein consumption occurred on June 8th, 2023, when protein intake spiked to a substantial 184.8 grams because both my breakfast and lunch contained more than 50 grams of protein, my dinner contained more than 40 grams, and my snack contained 30 grams.

The analysis of protein intake in relation to productivity presents a complicated picture. The significance scores, gauging the statistical strength of these patterns, were relatively high at 0.6579 for productive time and 0.5966 for unproductive time, suggesting a relatively weak link between protein intake and productivity measures. It's noteworthy, however, that the slope for protein intake when plotted against productive time was 12.19, indicating that for every additional gram of protein consumed, productive time increased by approximately 12 seconds (See Figure 19). Although the significance scores were high, suggesting a weaker statistical relevance, the positive slope underlines an important consideration: a potential positive correlation between protein intake and productivity. However, it's crucial to remember that this does not necessarily mean that higher protein intake causes increased productivity. It might be that other factors are involved or meals with lots of protein typically occur at the same time as productive hours, which I will be exploring further in 5.2.

When analyzing the three meals that resulted in the most productive times, I saw a basic trend of relatively low sugar consumption, some higher fat consumption, and a larger mix of complex carb and protein consumption. However, the actual caloric intake seemed to vary tremendously between these meals (See Figures 20, 21, and 22). Additionally, there were a few anomalies in which high sugar consumption resulted in high productive times (See Figure 23). However, these instances were likely due to the low quantities of calories consumed.

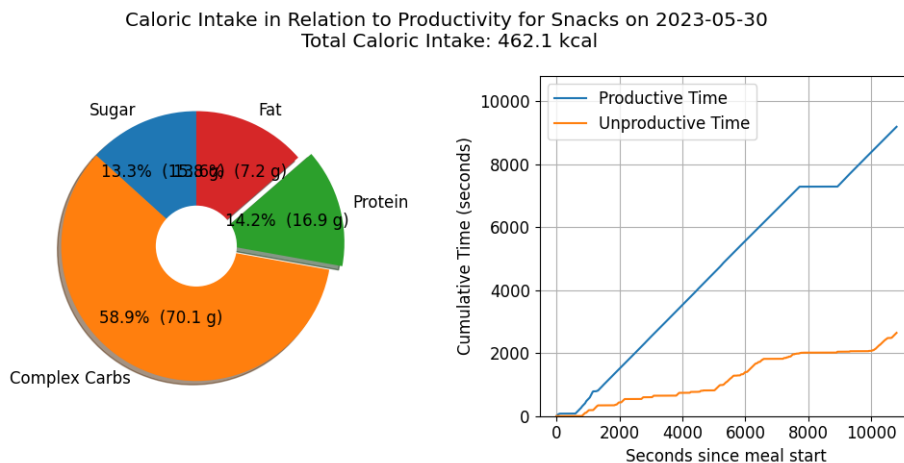


Figure 20. Plot containing pie chart of macronutrient intake (left) and line graph depicting productive and unproductive time (right) through the three-hour (10800-second) postprandial period (1).

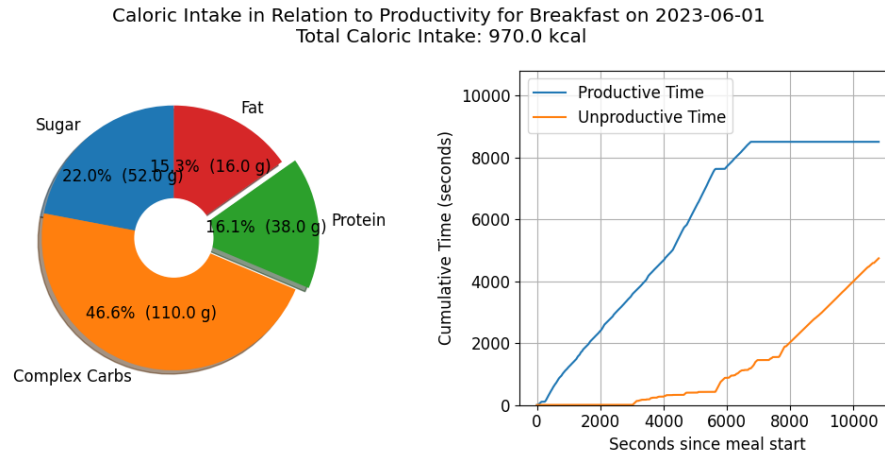


Figure 21. Plot containing pie chart of macronutrient intake (left) and line graph depicting productive and unproductive time (right) through the three-hour (10800-second) postprandial period (2).

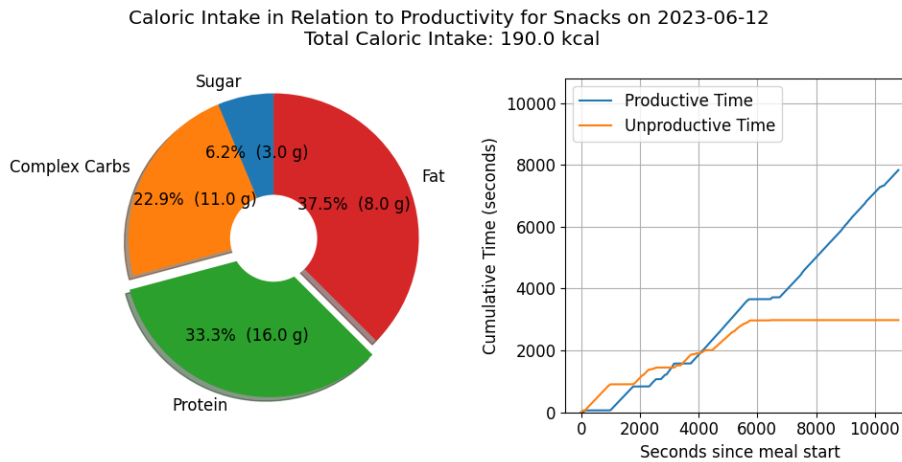


Figure 22. Plot containing pie chart of macronutrient intake (left) and line graph depicting productive and unproductive time (right) through the three-hour (10800-second) postprandial period (3).

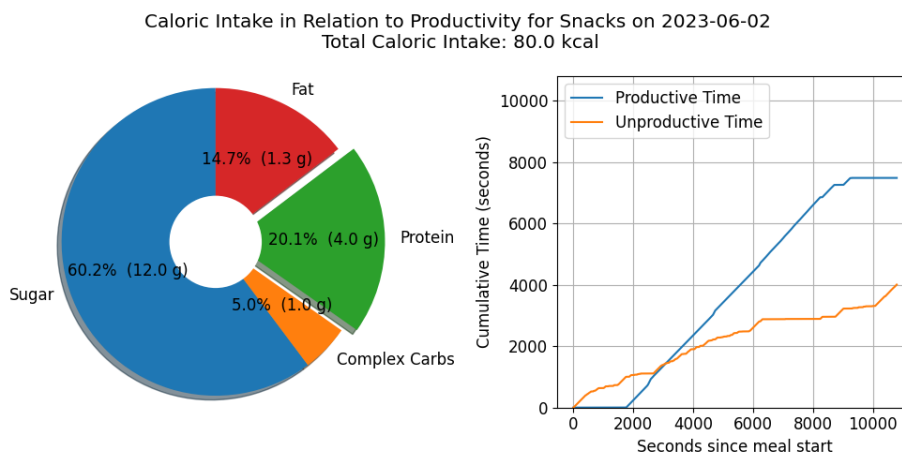


Figure 23. Plot containing pie chart of macronutrient intake (left) and line graph depicting productive and unproductive time (right) through the three-hour (10800-second) postprandial period (Anomaly).

The slopes of the unproductive switches graphs presented unexpected results. The only macronutrient that produced a positive slope of unproductive switches, a rather undesirable feature upon assumption, was protein, with a slope of 0.028. Even though it was the only macronutrient that had a positive productive time score, my unproductive switches seemed to increase as I consumed protein. Complex carbohydrates had an unproductive switches slope of -0.0417, sugar had a slope of -0.0466, fat had the most negative slope of -0.124, and calories had a slope of -0.0046. All of these values are very close to 0, indicating no apparent correlation between the variables.

Effects of Meal Timing and Time of Day on Productivity

My analysis provided compelling insights into the effects of meal timing and type on productivity. Across the board, the average meal times were approximately 10:54 AM for breakfast, 1:26 PM for lunch, 8:40 PM for dinner, and 4:32 PM for snacks. The productive time associated with these meals was quite varied; breakfast was linked with roughly 1.11 hours, lunch with about 1.05 hours, dinner with approximately 0.44 hours, and snacks with approximately 1.12 hours.

When assessing the correlation of meal start time with productive time, the significance score was impressively low at 0.00086939, indicating a very strong statistical relationship. Similarly, the correlation between meal-type and productive time yielded a relatively low significance score of 0.06391724, further underscoring the potential influence of meal timing on productivity. As I was aware that I consumed a higher protein ratio during breakfast and lunch, I also knew that I just typically enjoy working more in the mornings and early afternoons, hence causing a correlation between protein intake and productivity. Figure 24 represents a heatmap of my productivity, with meals shown in black.

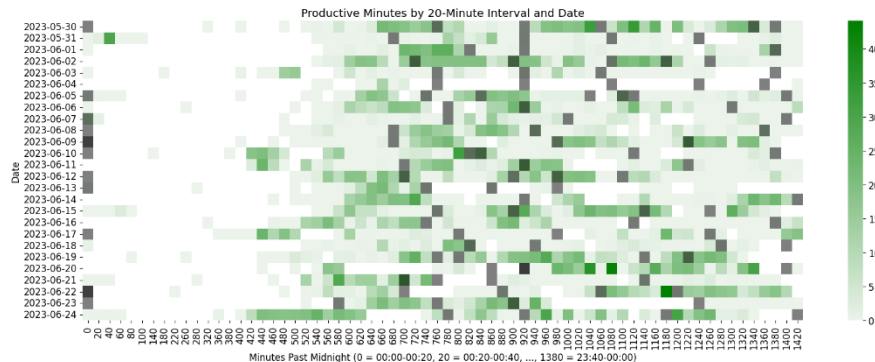


Figure 24. Heatmap of productive time with meals shown in black (20-Minute Intervals). White rectangles depict zero productive time, and the color of a given rectangle gradually changes more towards green as the productive time during that 20-minute period increases.

The pattern was somewhat mirrored when looking at unproductive time. The correlation of meal start time with unproductive time yielded another remarkably low significance score of 0.00766022, suggesting a strong link. However, the correlation between meal-type and unproductive time was notably weaker, with a significantly higher significance score of 0.63421018. Throughout the day, it seemed as though my unproductive time was relatively spread out, so the significance score between meal start time and unproductive time is quite surprising. Figure 25 represents a heatmap of my unproductive time, with meals shown in black.

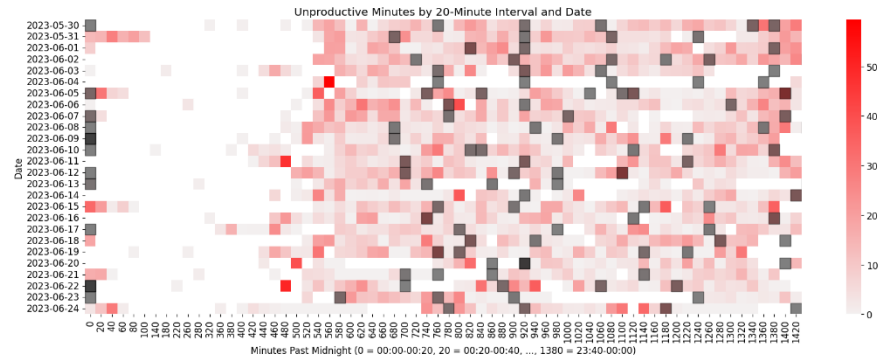


Figure 25. Heatmap of unproductive time with meals shown in black (20-Minute Intervals). White rectangles depict zero unproductive time, and the color of a given rectangle gradually changes more towards red as the unproductive time during that 20-minute period increases.

Taken together, these results indicate that the start time of meals may have been responsible for the correlations seen in 5.1, and my routine, in general, may have a more substantial influence on both productive and unproductive time than the type of meal consumed. These findings open exciting avenues for optimizing meal schedules to maximize productive time and reduce unproductive time, although further studies are needed to better understand the nuances of these relationships and their implications for daily routines and dietary habits.

Discussion

The exploration of dietary factors, meal timing, and productivity yields intriguing results, prompting implications and future areas of research. This section explores the potential reasons behind these outcomes, rooting them in the broader context of scientific literature.

The positive correlation between protein intake and productivity might be grounded in the impact of protein's constituent amino acids on neurotransmitter synthesis. Amino acids like tryptophan and tyrosine are precursors to serotonin and dopamine, neurotransmitters crucial for mood regulation, cognition, motivation, and reward processing. Serotonin is associated with a calming effect and the regulation of sleep, whereas dopamine is commonly known as a 'feel-good' neurotransmitter, directly influencing motivation and reward-driven behavior. The rise in these neurotransmitters following protein intake could enhance motivation and focus, thereby improving productivity (Fernstrom, 2005). Moreover, proteins are known for their satiating effects. Protein-rich meals tend to keep us feeling full for longer periods, reducing the likelihood of distraction by hunger and potentially improving focus and productivity. This sustained satiety could provide a stable energy supply conducive to maintaining productivity levels over an extended period.

However, the association of protein intake with an increase in unproductive switches presents an interesting insight. Upon plotting the regression between unproductive switches and productive time, the data displayed a positive correlation between the two variables, indicating that as unproductive switches increase, so does productive time (See Figure 26). The cause for this correlation lies in the very same logic that makes this metric, unproductive switches, inaccurate in deriving conclusions about productivity. If, for example, I spend all three hours of the postprandial period on my iPhone using TikTok, I will have unproductive switches count of 0, because I did not have a productive application to switch from in the first place. Hence, when I have a higher productive time value, I, in turn, have a higher chance of switching to an unproductive application.

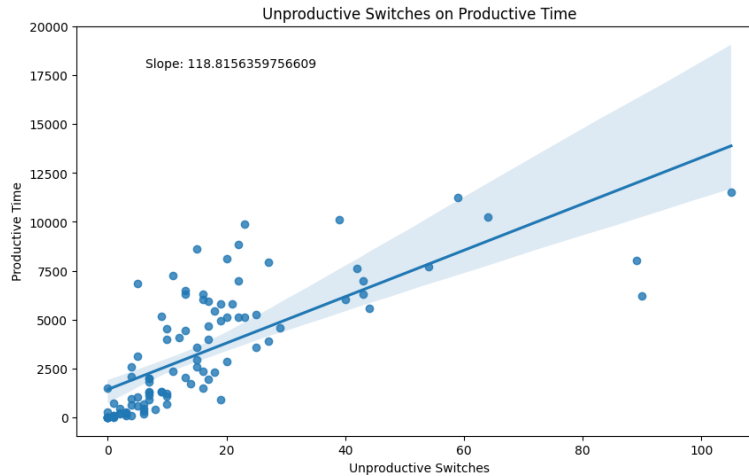


Figure 26. Impact of unproductive switches on productive time.

The negative correlation between carbohydrate intake and productivity introduces additional complexity. Distinguishing between simple and complex carbohydrates provides a potential rationale. Simple carbohydrates are digested quickly, leading to a rapid spike in blood sugar followed by a sudden drop, often referred to as a sugar crash (See Figure 3). Such crashes can lead to fatigue and concentration lapses, negatively affecting cognitive performance (Nilsson et al., 2012). Initial increases in blood glucose can aid in immediate productive spurts; however, these crashes lead to sudden losses. The study's link between fat intake and productivity is intriguing, and several factors might be at play. The inverse relationship discovered between fat intake and productivity is equally fascinating. Consumption of fats, specifically detrimental types such as saturated and trans fats, may incite a 'food coma,' which can curtail alertness and focus. Moreover, high-fat foods typically possess a high caloric content. Excessive consumption of these foods can provoke discomfort, thereby introducing an element of distraction from productive pursuits. Additionally, chronic exposure to a high-fat diet has been implicated in impairments in memory and learning capacities, which could insidiously erode productivity over an extended timeframe (Francis & Stevenson, 2013).

Our findings also underline the crucial role of meal timing and routine in cognitive function. The observed robust correlation between meal timing and productivity supports previous research showing the profound influence of circadian rhythms on cognition. Circadian rhythm refers to the physical, mental, and behavioral changes that follow a 24-hour cycle, primarily responding to light and darkness in an organism's environment. Our internal biological clocks govern a wide range of physiological processes, including digestion and hormone release. Disruptions to these rhythms, possibly through irregular eating patterns, can lead to metabolic dysregulation, which subsequently impacts cognitive performance. On the other hand, working through a routine that is supported by one's circadian rhythm may actually increase productivity and efficiency (Harrington, 2001). Moreover, the correlation between meal timing and productivity may be partially attributed to the interplay between dietary habits and daily routines. For instance, a consistent meal schedule may enhance feelings of control and order, reducing cognitive load and enabling more focused attention on tasks. These routines could create an environment conducive to productivity, suggesting a psychosocial dimension to our findings.

An additional interesting insight can be seen in Figure 27 and in many other instances. Throughout the rough range of 1000 seconds (about 17 minutes) and 4200 minutes (about 70 minutes), both my productive times and unproductive times were increasing (See Figure 27). This may be due to a few reasons. First, perhaps when my Python code was running, I would go on my phone and watch some TikTok, or maybe when I was watching Netflix, I would also think about getting some work done. However, when Timing App does not sense any application engagement for 3 minutes, it automatically stops tracking time. This feature eliminates the possibility of leaving my computer open for a productive application without actually using it.

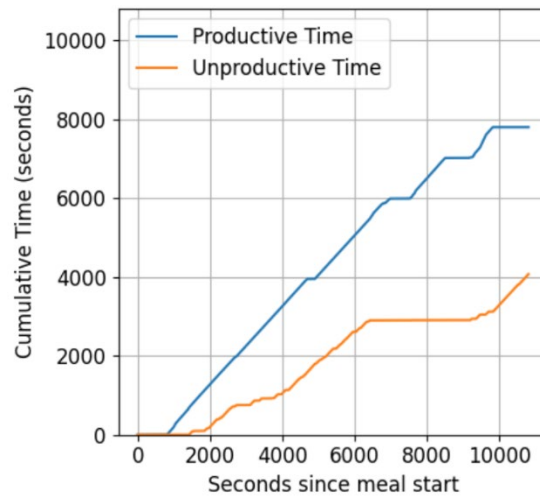


Figure 27. Sample productive and unproductive time line graph. Both productive time and unproductive time can be increasing suddenly at the same time.

In conclusion, this research adds to the growing body of evidence pointing toward the role of diet, meal timing, and routine in influencing productivity. Although there exists a very real correlation between macronutrient consumption and my own productivity, I am unable to guarantee that the actual macronutrients themselves are responsible for the shift in productive and unproductive times. Rather, meal timing and routine in general seem to have a greater impact on productive and unproductive time. Future studies could seek to replicate and extend these findings to larger, more diverse populations. Moreover, more controlled experimental designs could help clarify the causal relationships suggested by this study and explore the potential mechanisms behind them.

Conclusion

This study has produced interesting insights into the impact of meals, meal timing, and macronutrient consumption on productivity. The potential influence of macronutrient intake on productivity emphasizes the value of a balanced diet, not just for general health but also for cognitive performance and workplace efficiency.

The study found that protein intake correlated positively with productivity, possibly due to the role of amino acids in neurotransmitter synthesis and protein's contribution to prolonged satiety, but more likely due to increased protein intake during breakfast and lunch. My daily routine, regardless of the actual meal, normally includes working in the morning and early afternoon. Despite this, an increase in unproductive switches was also observed with increased protein intake, illustrating the complexities inherent in defining and measuring productivity. On the other hand, carbohydrate intake showed a negative correlation with productivity. This outcome highlighted the differences between simple and complex carbohydrates, their impact on blood glucose levels, and their subsequent effects on cognitive performance, as simple carbohydrates decreased productivity at around twice the rate of complex carbohydrates. Furthermore, high-fat intake was linked with decreased productivity, a result that provokes questions about the effects of different types of fats and their impact on post-meal fatigue and cognitive function.

Of all the factors examined, meal timing displayed the strongest correlation with productivity, highlighting the significant role circadian rhythms play in cognitive function and the potential influence of a regular meal schedule on cognitive performance. The data showed that maintaining consistency in meal times could enhance productivity, suggesting a connection between dietary habits and daily routines.

For future research, it would be beneficial to conduct larger-scale studies with a more diverse sample size to validate these findings. However, in doing so, this approach would take away from the Quantified Self aspect of this

paper. Additionally, I would like to go more in-depth on time of day and routine and how these factors affect productivity and time management. Furthermore, the potential influence of other lifestyle factors such as exercise, sleep, stress management, and net caloric difference, which would consider our body's physical caloric expenditures as well as intake, could be explored to gain a more holistic understanding of the many variables that contribute to productivity. As our understanding of these relationships deepens, so will our ability to effectively enhance cognitive performance and productivity through targeted dietary and lifestyle interventions.

In conclusion, the results of this study demonstrate the intricate interplay between diet, routine, and cognitive performance and how these relationships can influence my productivity in the three-hour period after eating a meal. The findings offer valuable insights for individuals seeking to optimize their dietary habits and routines to improve productivity and for workplaces aiming to support the cognitive well-being and efficiency of their employees.

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