Fundusze Europejskie
Wiedza Edukacja Rozwój
Rzeczpospolita Polska
Unia Europejska
Europejski Fundusz Społeczny

SWPS University of Social Sciences and Humanities
Institute of Psychology

Aleksandra Bramorska

The effect of diet and gut microbiota on cognitive functioning.

PhD Thesis
Thesis supervisor: *prof. SWPS, dr hab. Aneta Brzezicka*
Auxiliary supervisor: *dr Bartłomiej Balcerzak*

Warsaw, 2023

SWPS University

Chciałabym podziękować za wsparcie i zaangażowanie wszystkim, bez których nie mogłabym napisać tej pracy.

prof. Uniwersytetu SWPS, dr hab. Anecie Brzezickiej,
za cenne rady, wsparcie oraz pełną życzliwości i wyrozumiałości postawę

dr Mirjam Bloemendaal
za całą pomoc, niezliczone konsultacje, wspieranie mnie podczas badań nad mikrobiotą i opiekę na stażu
I would like to thank dr. Mirjam Bloemendaal
for all your help, numerous consultations, support during my microbiota research and internship supervision

prof. Alejandro Arias Vasquez
za wsparcie merytoryczne i goszczenie mnie w swoim zespole w Donders Institute for Brain, Cognition and Behavior w Nijmegen
I would like to thank prof. Alejandro Arias Vasquez
for insightful advice and hosting me in his laboratory during my internship at the Donders Institute for Brain, Cognition and Behavior in Nijmegen

dr Katarzynie Kuć
za merytoryczne konsultacje i dodawanie otuchy

Wandzie Zarzyckiej,
za ogromną życzliwość i wyrozumiałość, pomoc w każdej sytuacji, niezliczone godziny spędzone wspólnie w laboratorium i tworzenie naszego zespołu

Wiktorii Podoleckiej
za pomoc w przeprowadzeniu badań na każdym etapie

Natalii Jakubowskiej i Justynie Józefowicz,
za wspólne podążanie ścieżką doktorancką, za motywację i inspirację

Karolinie Barańskiej
za inspirujące rozmowy i słowa otuchy w każdej sytuacji

Beci, siostrze
za wsparcie, życzliwość, poczucie humoru i że zawsze mogłam liczyć na Twoją pomoc

Rodzicom
za miłość, wsparcie i wiarę we mnie

The study was funded by the grants awarded to the University of Social Sciences and Humanities in Warsaw.

Statutory Grant of Polish Ministry of Science and Higher Education (Republic of Poland) to SWPS University of Social Sciences and Humanities in Warsaw – BST grant no WP/2018/A/90

"Regionalna Inicjatywa Doskonałości” in the years 2019-2022, RID grant no 012/RID/2018/19

Table of contents

Abstract

Problem: The purpose of this study was to examine the impact of dietary patterns on different cognitive functions and how they influence the cognitive ageing process. In addition, the relationship between cognitive functioning and gut microbiota (extracted from feces samples) was examined in a cohort of 68 female participants. Another aim of the thesis was to determine the predictive value of the described dietary patterns - especially factors that potentially promote or impair cognitive functioning - and whether the gut microbiota might influence this relationship. It is important to note that this thesis focuses on a group of healthy individuals with varying diets and dietary patterns, although often such studies are carried out with children, the elderly, or patients with intestinal or psychiatric problems.

Methods: Two studies were conducted. The first study investigated the association between the dietary patterns of 202 subjects following a conventional diet and their performance on a cognitive task involving working memory. The second study consisted of two phases. In the first part, 396 individuals with varying diets and dietary patterns participated, and the relationships between a person's dietary habits and cognitive tasks involving working memory and spatial memory were examined. In the second part of the study, 68 women were selected from the initial group of 396 participants for microbiota testing. The selection was based on their diet (conventional or vegetarian) and diet quality, which was determined using the unhealthy diet index extracted from the Food Frequency Questionnaire. The study examined the relationship between dietary patterns, gut microbiota, and various cognitive processes, including episodic memory, verbal memory, and working memory.

Results: The analyses revealed that dietary patterns have an impact on the performance of various cognitive processes. It has been demonstrated that consuming different types of meat and meat products can mitigate the age-related decline in working memory performance, as well as the negative effects of obesity on spatial memory task. Additionally, it was also

observed that an unhealthy dietary pattern characterized by the consumption of fast food, high-sugar beverages, confectionery, and other similar items, had a detrimental effect on episodic memory performance. Furthermore, the diversity of the gut microbiota was found to have a positive influence on episodic memory performance. However, no significant correlation was found between diet, gut microbiota, and cognitive task performance.

Conclusions: The findings of this study suggest that dietary habits can either enhance or impede cognitive functioning and that this impact is more evident in the older population. Consuming red meat negatively impacted cognitive performance of the memory search sub-task, whereas eating fish and white meat improved its performance. Literature results regarding meat consumption are not yet completely consistent. Some studies indicate that consuming less red meat is associated with better cognitive function (Zupo et al., 2022), whereas others suggest that consuming more red meat, particularly unprocessed meat, enhances cognitive function (H. Zhang et al., 2021). Based on a meta-analysis (Quan et al., 2022) it seems that the technique of preparation of the meat meal appears to be critical when it comes to its impact on cognition. The results presented in this thesis support such conclusion. In addition, the consumption of processed foods has been associated with impaired cognitive functioning, particularly episodic memory, which is supported by the literature on this topic (Noble et al., 2017). The diversity of the gut microbiota had a positive effect on the episodic memory task, indicating that the gut microbiota is a key component for brain and cognitive functioning (Noble et al., 2021). The absence of an association between gut microbiota, diet, and performance on various cognitive tasks, as found in the presented studies, suggests that diet and gut microbiota affect cognitive functions through separate mechanisms.

Key words: cognitive functioning, memory, ageing, diet, protective and detrimental dietary habits, gut microbiota

Streszczenie

Problem: Celem niniejszej pracy było sprawdzenie związku pomiędzy funkcjonowaniem poznawczym a dietą, wyszczególnienie i opisanie zależności między wzorcami żywieniowymi a przebiegiem róznych procesów poznawczych. Dodatkowo, obszarem zainteresowania pracy było sprawdzenie zależności pomiędzy funkcjonowaniem poznawczym oraz mikrobiotą jelitową (wyodrębnioną z próbek kałowych) w grupie kobiet. Prezentowane analizy miały na celu sprawdzenie wartości predykcyjnej opisywanych wzorców żywieniowych - czynników, które wspierają oraz zaburzają funkcjonowanie poznawcze i odpowiedź na pytanie, czy mikrobiota jelitowa może być czynnikiem moderującym te zależności. Ważnym podkreślenia jest fakt, że badanie skupiło się na grupie zdrowych osób, różniących się dietą i sposobem odżywiania, podczas gdy zazwyczaj takie badania prowadzone są z udziałem dzieci, osób starszych, pacjentów z chorobami jelitowymi czy psychiatrycznymi.

Metoda: Przeprowadzone zostały dwa badania. W pierwszym wzięły udział 202 osoby badane na diecie konwencjonalnej i zbadano zależności pomiędzy wzorcem żywieniowym tych osób a zadaniem poznawczym związanym z pamięcią roboczą. Drugie badanie zostało podzielone na dwa etapy. W pierwszym etapie wzięło udział 396 osób z różnymi dietami i sposobem odżywiania. Sprawdzono zależności pomiędzy wzorcem żywieniowym osób a zadaniami poznawczymi związanymi z pamięcią roboczą oraz pamięcią przestrzenną. W drugiej części badania, z grupy 396 osób wyodrębnionych zostało 68 kobiet do badań mikrobioty, na podstawie informacji o ich diecie (konwencjonalnej lub wegetariańskiej) i z uwzględnieniem jakości diety według wskaźnika niezdrowej diety wyodrębnionego z kwestionariusza Food Frequency Questionnaire. Sprawdzono zależność pomiędzy wzorcami żywieniowymi, mikrobiotą jelitową a szeregiem zadań poznawczych związanych z różnymi procesami poznawczymi: pamięcią epizodyczną, pamięcią werbalną oraz pamięcią roboczą.

Wyniki: W trakcie analiz określone zostały wzorce żywieniowe, które wpływają na działanie rożnych procesów poznawczych. Wykazano, że spożywanie różnych rodzajów mięsa oraz produktów mięsnych może moderować efekt wieku w zadaniu związanym z pamięcią roboczą oraz wpływ otyłości na wykonanie zadania pamięci przestrzennej. Zaobserwowano także negatywne znaczenie niezdrowego wzorca żywieniowego (produkty związane z żywnością wysoko przetworzoną, taką jak fast food, wysokocukrowe napoje i słodycze) w wykonaniu zadania związanego z pamięcią epizodyczną. Wykazano również, że różnorodność mikrobioty jelitowej pozytywnie wpływa na wykonanie zadania związanego z pamięcią epizodyczną. Nie znaleziono związku pomiędzy dietą, a mikrobiotą jelitową w odniesieniu do wykonania zadań poznawczych.

Wnioski: Przeprowadzone badania pozwalają wnioskować, że odpowiednie nawyki żywieniowe mogą wspierać lub pogarszać funkcjonowanie poznawcze a także, że związki te staja się wyraźniejsze, gdy badamy starszą populację. W podzadaniu przeszukiwania pamięci czerwone mięso dawało negatywny związek z wykonaniem zadania poznawczego, za to spożywanie ryb i białego mięsa sprawiło, że osoby te osiągały w tym zadaniu lepsze wyniki. Wyniki dotyczące spożywania mięsa nie są jeszcze w literaturze do końca spójne. Niektóre badania wskazują, że mniejsze spożycie czerwonego mięsa jest związane z poprawą funkcjonowania poznawczego (Zupo et al., 2022), podczas gdy inne wskazują, że to większe spożycie czerwonego mięsa, szczególnie nieprzetworzonego, poprawia funkcje poznawcze (H. Zhang et al., 2021). Na podstawie metaanalizy (Quan et al., 2022) wyciągnięto wnioski, że kluczowe znaczenie wydaje się mieć sposób przygotowania mięsnego posiłku. Uzyskane wyniki wspierają ten wniosek. Ponadto, wykazano, że spożywanie żywności przetworzonej i ilość spożytych kalorii pochodzących z żywności przetworzonej wiąże się z obniżeniem funkcjonowania poznawczego, szczególnie w obrębie pamięci epizodycznej, co także wspiera literatura dotycząca tego tematu (Noble et al., 2017). Różnorodność mikrobioty jelitowej pozytywnie wiązała się z wykonaniem zadania mierzącego pamięć epizodyczną, co także wskazuje, że mikrobiota jelitowa jest ważnym elementem dla działania mózgu i wspiera funkcjonowanie poznawcze (Noble et al., 2021). Brak powiązania pomiędzy mikrobiotą jelitową i dietą a wykonaniem zadań poznawczych może wskazywać, że są to oddzielne procesy wpływające na funkcjonowanie poznawcze.

Słowa kluczowe: funkcjonowanie poznawcze, pamięć, starzenie się, dieta, ochronne i szkodliwe nawyki żywieniowe, mikrobiota jelitowa

Introduction. Food ingestion and cognitive functioning

Humans require sustenance to supply their bodies with the nutrients and energy required for the maintenance and regulation of bodily functions (Chen et al., 2018; Munteanu & Schwartz, 2022; Weyh et al., 2022). Food also serves essential for social and cultural functions (Higgs & Thomas, 2016), so it is not always hunger that motivates individuals to eat (Beaulieu & Blundell, 2021; P. M. Smith & Ferguson, 2008). Meals are shared with family and friends, making them essential for obtaining happiness in daily life and preserving mental health (Plassmann et al., 2022). Smyth et al. (2015) found that those who had a healthier diet had a lower risk of cognitive deterioration as they aged (Smyth et al., 2015). In addition, antioxidant flavonoids from berries consumption is linked to enhanced cognitive functioning in the elderly (Devore et al., 2012).

Cognitive functioning refers to mental processes such as thinking, learning, language, reasoning, attention and concentration, memory, and executive functions (Harvey, 2019; Kumar et al., 2022). Cognitive functioning can be enhanced or impeded by factors that contribute to task performance, such as motivation, food, mood, or aging (Ferdinand & Czernochowski, 2018; Murman, 2015; Salthouse, 2010; Scholey & Owen, 2013). Even healthy aging causes a progressive deterioration in cognitive performance (Salthouse, 2006), for instance, attention and concentration-demanding tasks show an age-related attenuation (Quigley & Müller, 2014). Executive functions are required for planning and organizing every aspect of daily life, and they decline with age (Fisk & Sharp, 2004). The function of working memory, the capacity to maintain and manipulate information (McNab et al., 2015), also declines with age. Further, memory impairment is the most generally reported condition in ageing participants, with episodic memory being the one most typically deteriorated (Nyberg et al., 2012).

However, it is not only aging that causes problems with cognition. Memory, information-processing speed, attention, executive functioning, and verbal memory are all affected in patients with diabetes (Palta et al., 2014), or metabolic syndrome (Grünblatt et al., 2011; Moheet et al., 2015). Interestingly, efficient cognitive functioning is critical for optimal food consumption, as well as for initiating and finishing a meal (Davidson et al., 2019). Meal size is determined by neural and endocrine homeostatic signals detected in the hypothalamus and hindbrain (Cifuentes & Acosta, 2022). However, higher neural systems also influence energy balance; the hippocampus receives inputs from the hypothalamus, and leptin and insulin receptors are expressed in this region (Morton, 2007). Memory affects daily food intake by mobilizing behavioral responses to food through hippocampal-dependent memory pathways (Suarez et al., 2019) and is crucial in the start and end of a regular meal. Rozin et al. (1998) observed, based on the behavior of two patients with bilateral damage to the hippocampus and amygdala, that a memory of what has been consumed may influence meal initiation and termination (Rozin et al., 1998). Higgs et al. (2002) demonstrated that recalling recently ingested food significantly decreased food consumption (Higgs, 2002). Oldham-Cooper et al. (2011) conducted a study on distractions during eating, such as watching television or playing computer games. Compared to the non-distracted group, the distracted participants consumed more biscuits and reported feeling less satiated immediately after lunch (Oldham-Cooper et al., 2011). Sedentary activity reduced meal memory quality, and yet the time spent sedentary is considered to play a crucial role in the development of excess adiposity (C. E. Matthews et al., 2012; Staiano et al., 2018). These results suggest that episodic memory may play a significant role in the regulation of a meal size and appetite (Brunstrom et al., 2012).

Cognitive processes such as learning and memory can influence food intake, based on previously acquired experience and the hedonic qualities of food (Beekman et al., 2022;

Higgs & Thomas, 2016). As opposed to homeostatic feeding, in which food is consumed to maintain energy balance, hedonic regulation of feeding may not be a response to a general energy deficit or other types of metabolic requirements (Lutter & Nestler, 2009). When a human eats a food that causes a pleased hedonic response, it would proceed to be linked with the positive (enjoyable) reaction through the quality of that food item (e.g. the look and smell) (Berridge, 1996). Learning through this pattern causes that the sightingths and smells linked with food are more likely to be looked for (Berridge, 1996).

Cognitive processes such as learning, attention, and memory have been linked to the everyday regulation of hunger (Higgs et al., 2017), and food motivation is dependent on cognitive modulation of reward processes (Small & DiFeliceantonio, 2019). It is worth noting that although food consumption is linked to cognitive processes, by no mean it implies that people consciously contemplate food decisions all the time - eating is a complex, unconcious cognitive process (Sato, 2020).

These homeostatic-metabolic controls of food ingestion are linked to a complex brain system involved in hedonic control of food intake, which assigns rewarding aspects to food items, allowing them to induce emotional reactions (Rossi & Stuber, 2018). This process is unconscious, driven by the coordination of hunger, satiety, and satiation and involves a large-scale modulation of food rewarding characteristics both during and between meals. Food-related sensory signals (sight, smell, taste, and texture) and interoceptive homeostatic signals (representing nutritional status) are integrated into cognitive-affective processes (Oliveira-Maia et al., 2011; Rolls, 2021). It determines a value and pleasure felt about food, which in turn affects eating behavior (Butler & Eckel, 2018; McCrickerd & Forde, 2016). In addition, Malaglada et al. (2015, 2016) in theirs studies, showed that the hedonic dimension of a meal includes cognitive aspects like conscious sensation of eating and identification of meal ingestion-related cognitive biomarkers (Malagelada et al., 2015, 2016). It may be a representation of the food consumption reward (Ciccantelli et al., 2017; Egecioglu et al., 2011). Insula has been suggested as the structure where conscious and unconscious processing overlap (de Araujo et al., 2013). Energy homeostasis is controlled by three basic caloric macronutrients: fat, carbohydrates, and protein (Carreiro et al., 2016). Li et al. (2012) showed that some brain structures - like the middle insula, thalamus, parahippocampal cortex, and lateral occipital frontal cortex - are similarly sensitive to the same amounts of macronutrients in food (Li et al., 2012).

The neural circuits in the central nervous system (CNS), which regulate energy balance (Gautron et al., 2015) are dependent on the relative levels of hunger, satiation, and satiety (Benelam, 2009). Satiation is the absence of hunger during a meal, whereas satiety is the sensation of satisfaction after a meal that gives way to hunger over a period of time (Morell & Fiszman, 2017). On the other hand, peripheral hormonal and neurological signals also provide energy status information (Kim et al., 2018). Both systems derive from the digestive tract, liver, and adipose tissue (Ahima, 2006; Janssen et al., 2011). Gut is the primary organ for digesting food, and as such, it is wired to detect size and substance of meals, playing a crucial part in regulating hunger (Cummings & Overduin, 2007).

The gut-brain axis consists of bidirectional communication between central and enteric nervous systems, linking emotional and cognitive centers of the brain with peripheral intestinal functions (Carabotti et al., 2015; Steinert et al., 2017; S. C. Woods, 2004). Based on these peripheral signals relayed to the brain, food intake, appetite and satiety are mainly integrated at the level of hypothalamic neuronal circuits (Carabotti et al., 2015). Neurons within the hypothalamus play critical roles in the homeostatic control of energy and body weight by adjusting energy intake to energy expenditure in response to biological and environmental cues (de Wouters d’Oplinter et al., 2022). The gut-brain axis influences the satiety and food intake (Maljaars et al., 2007).

Digestive system responds to food consumption (Livovsky et al., 2020) in several steps: 1. presence of food in the stomach causes distension; 2. nutritional components such as lipids, proteins, carbohydrates, and their digestive products are exposed to the small intestine lumen at increasing rates while gastric emptying continues and inputs from mechanical distension decrease progressively; 3. the unabsorbed nutrients from meal reach colon and stimulate metabolism of resident microorganisms (Hajishafiee et al., 2019). Then, hormonal peptides in the gastrointestinal (GI) tract function as a link between the endocrine and nervous systems, regulating brain function and eating behavior. The hypothalamus in the CNS receives metabolic information from hormones and peptides secreted by the gut in response to food and its macronutrient composition (Wachsmuth et al., 2022). In order to regulate appetite, the GI tract secretes a number of hormones that function as a signal of hunger or satiation to the CNS. These hormones include appetite-stimulating hormones such as ghrelin and satiety-stimulating hormones such as leptin (Zanchi et al., 2017).

The homeostatic and hedonic circuits communicate with one another, but under stress or in conditions such as anorexia, depression, or anxiety, this exchange can be impaired (Liu et al., 2023). Moreover, excessive consumption of pleasurable foods may trigger neuroadaptive responses in the brain's reward circuitries that are analogous to those induced by addictive substances (de Macedo et al., 2016; Kenny, 2011). The cortico-limbic regions of the brain, which are involved in functions like learning and memory, are particularly vulnerable to the effects of environmental nutrient depletion signals (H. Zheng et al., 2009). The sensory qualities of food used to be a good indicator of its energy and nutrient content. Recent developments in food technology allowed for the mass production of food (like snacks) in which sucrose polyester has been used to replace fat while aspartame has been used to replace sugar (Grossman et al., 1994; Stubbs, 1999). The prevalence of artificial stimulants in modern diets makes it difficult to estimate the quantity of calories from its sensory characteristics (Davidson et al., 2019). Identifying energy sources is dependent on cognitive processes that build links between dietary cues and their nutritional value (Davidson et al., 2019). As a result, previously related caloric signals activate neurons in the nucleus accumbens (de Araujo et al., 2013). The motivational component of nutrition learning is controlled by metabolic signals generated during and after digestion (Petrovich, 2011). Many of the physiologic signals believed to regulate feeding are activated by nutrient consumption, and feeding behavior is influenced by diet composition (Assan et al., 2021; Hopkins et al., 2000). Eating disorders, including those that result in obesity, are characterized by imbalance between hedonic and satisfying values assigned to food and energy needs (Jiménez-Murcia et al., 2019). Therefore it is useful to study peripheral appetite signals in the context of energy and nutritional balance.

Diet can affect learning and memory throughout a lifespan. There is a negative association between the quality of a diet and disorders that affect hippocampal-dependant memory (Suarez et al., 2019). Hsu et al. (2014) found that rats fed on the Western diet (WS diet), with lots of saturated fats and refined sugars, had decreased memory capabilities and more inflammation in their brains (Hsu & Kanoski, 2014). High fat and sugar intake is linked to problems with learning and memory that depend on the hippocampus in children (Baym et al., 2014), adults (Attuquayefio et al., 2017) and elderly (Morris et al., 2006). This suggests that the WS diet has a negative effect on the function of the hippocampus throughout the lifespan.

The gut microbiota is an important part of the gut-brain axis, which links the digestive tract to brain development and functioning (Dinan et al., 2015; Fernandez-Real et al., 2015; Forsythe et al., 2016). It is made up of an estimated 100 trillion microorganisms that live in the host's GI system (Cryan et al., 2019). Dietary factors affect the gut microbiome ((Noble et al., 2021; Petersen et al., 2019), and the gut microbiota has emerged as a major contributor to cognitive health (Bloemendaal et al., 2021). In addition, many studies have found a link between the composition of gut microbiota and stress as well as affective disorders such as anxiety, depression, and cognitive impairment (Dinan & Cryan, 2012). O'Mahony et al. (2015) show that a balanced microbiota in the gut has a role in serotonin metabolism regulation (O’Mahony et al., 2015). Furthermore, stress may influence and alter the gut microbiota, which may have a negative impact on digestive health (Bravo et al., 2011). Therefore, maintaining cognitive performance throughout life may depend on having a healthy, well-balanced diet that helps to manage the gut microbiota, as well as reduce inflammation in the brain, and sustains the body (Marques et al., 2018; Noble et al., 2017; Spencer et al., 2017; Suarez et al., 2019). Moreover, Blasco et al. (2017) showed the association between brain iron deposition and the effects of weight loss. Brain iron deposition in the striatum, amygdala, and hippocampus were associated with changes in waist circumference, but not in body mass index and these changes were linked to shifts in gut microbiome (Blasco et al., 2017).

Although genetics and environmental factors, such as lifestyle, influence the composition of gut microbiota, diet and nutrition appear to be among the primary drivers of gut microbiota composition and functioning (Kolodziejczyk et al., 2019; Turnbaugh et al., 2006). Diet can be a modifiable determinant of gut microbiota composition, as it has been shown to directly shape microbiota in both rodents and human studies (Petersen et al., 2019; Seel et al., 2023). High-fiber diets and the Mediterranean diet, for instance, have been associated with a lower risk of depression because they support a diversity of gut microbiota (Sonali et al., 2022). Gut microbiota may be influenced by eating fermented foods (Kolodziejczyk et al., 2019). Although the gut microbiota may have an effect on mental health, the mechanisms by which this occurs are not yet well understood (Cryan et al., 2019).

Aims of the thesis

The aim of the doctoral research was to explore the relationship between dietary habits, gut microbiota, and cognitive performance in a group of adults from the general population. Dietary preferences among adults are rather diverse, ranging from health-oriented eating plans to animal-free diets for environmental reasons. Simultaneously, highly processed foods contribute to obesity and poor eating habits. Since the gut microbiota develops as a result of dietary input, different microbial profiles are a result of increased or decreased plant and meat consumption. Furthermore, the microbiota-gut-brain axis emphasizes that the commensal gut microbiota have an impact on mental health and performance.

However, not enough research has been done on how these kinds of differences in diet affect cognitive performance in adults in the general community. The gut-brain effects are generally researched by older adults and school-aged children in extreme settings, such as early-life infections or neurodevelopmental or psychiatric patients.

Thesis road map

In the following text I will briefly introduce the chapters of this doctoral dissertation thesis. It begins with the introduction and general overview of the rationale for the thesis, emphasizing the significance of unconscious cognitive processes in relation to eating behaviors. Following the opening, it will proceed to description of the first study that was conducted to estimate the effects of healthy and unhealthy food products on cognitive functioning of healthy adults. I will first describe the significance of diet to cognitive function, followed by a detailed account of the research methods, findings, and a brief summary. In the next chapter I proceed to the second study description which was an expansion of the first study to incorporate the topic of a gut microbiota. I intended to explore the influence of bacteria on cognitive functioning, because the gut microbiota may be able to modulate the association between nutrition value of food and cognitive functioning. The study was separated into two parts. In a manner comparable to the first study, in the first step I analyzed the effect of diet on cognitive performance. The following step was to recruit 68 participants from the initial, bigger group to participate in a detailed, microbiota study. I will therefore present the results separately for each part, followed by a joint summary. In a concluding discussion, the results from both studies will be summed up.

1. Study 1. Relationship between dietary patterns and age-related cognitive decline

1.1. How does diet influence cognition?

The gut–brain axis consists of bidirectional communication network that monitors and integrates gut functions and links them to cognitive and emotional centers of the brain (Dam et al., 2019). Diet can also heavily influence cognitive and emotional functioning. Certain vegetables and fruits contain polyphenols, which when consumed may lower inflammation, leading to better cognitive functioning (Devore et al., 2012; Mao et al., 2019). Memory, cognitive control, attention, and working memory are only a few of the cognitive traits that have been linked to age-related cognitive decline (Harada et al., 2013; Rey-Mermet & Gade, 2018; Salthouse, 2009). Dietary habits are particularly important when taking into consideration the process of aging, with the consumption of these food products providing better cognitive function in older age (Spencer et al., 2017). Diet is an important factor in mental health and cognitive abilities (Adan et al., 2019; Loughrey et al., 2017; Rodrigues et al., 2020), as well as in the avoidance and treatment of chronic diseases (e.g., obesity, diabetes, and cardiovascular disease) (Martínez-González et al., 2019; Martín-Peláez et al., 2020).

The Mediterranean diet (MD) is widely regarded as one of the best dietary models for healthy aging, with research demonstrating that it lowers risk factors for cardiovascular disease and dementia, among other things (Loughrey et al., 2017). MD diet is an antioxidant-rich eating pattern that has been found to lessen the likelihood of dementia and other mental deterioration (Petersson & Philippou, 2016). Omega-3 polyunsaturated fatty acids (PUFAs) are found in abundance in fatty fish, and these fatty acids have been shown to protect nerve cells. PUFAs have a key role in sustaining brain function, such as synaptic plasticity or neurotransmission regulation (Bazinet & Layé, 2014), and lipids are essential for the development of the central nervous system (Madore et al., 2020). Omega-3 polyunsaturated fatty acids may help increase memory ability by strengthening functional hippocampus connections (Huhn et al., 2015). Indeed, in a literature adherence to the MD diet was associated with a lower risk of cognitive impairment, and increased fish consumption was similarly correlated with slower cognitive decline within the MD diet. However, Samieri et al., 2013 found no relationship between following the Mediterranean diet and better cognitive performance (Samieri et al., 2013).

A diet may also have detrimental effects on particular functions, namely cognition, memory and learning (Cordner & Tamashiro, 2015). The Western Style (WS) diet, rich in refined carbohydrates and saturated fats, can cause neuroinflammation and significant damage to hippocampus, leading to the impairment of hippocampal-dependent memory (Hsu & Kanoski, 2014; Kanoski et al., 2010; Suarez et al., 2019). Hippocampus may be directly impacted either by unhealthy food products or by diseases that are related with WS diet and eating habits, such as diabetes or obesity (Noble & Kanoski, 2016). In addition to hippocampus role in memory and learning, the hippocampus also regulates gastrointestinal function (Suarez et al., 2019). Weaker inhibitory control and an increase in consumption of high-fat food and weight gain (Sample et al., 2016; Stevenson et al., 2020), in consequence, follow from the WS diet negative effects on hippocampal function and memory performance (Baym et al., 2014; Hassevoort et al., 2020). This has been linked to the increase in high-energy meals consumption (especially those high in saturated fat). Just four days on the WS diet was enough to increase blood glucose levels and negatively impact memory performance (Attuquayefio et al., 2017). In another study, rats were fed a high-fat diet for a short period of time, and their memory was found to be impaired due to an increase in corticosterone levels in the hippocampus (Sobesky et al., 2016). Glucose in the blood can increase cognitive performance, especially memory (M. A. Smith et al., 2011), but the quality and quantity of food converted into glucose in the body are crucial (Small & DiFeliceantonio, 2019). The WS diet lacks critical polyphenols and antioxidants, may be deficient in beneficial omega-3 PUFAs (Noble et al., 2017), and may reduce mood and cognitive function (Kanoski & Davidson, 2011).

In older age, WS diet may lead not only to cognitive function impairment, but also the emergence of neurodegenerative disorders, such as Alzheimers or Parkinson’s disease (Francis & Stevenson, 2013a; Kanoski & Davidson, 2011; Noble et al., 2017). Due to the potential negative impact of an unhealthy diet on cognition, it is important to consume food products high in nutrients and other healthy substances (Attuquayefio et al., 2017; Petersen et al., 2019). One such group are polyphenols, which can be split into flavonoids and no-flavonoids (Bertelli et al., 2021). They can be mostly be found in, for example, cocoa and fruits (Laveriano-Santos et al., 2022; Penczynski et al., 2019). Studies have shown that food products high in polyphenols may improve attention, working and spatial memory (Lamport, 2012). Anthocyanins, a type of flavonoid found in berries, yogurt and red vegetables, play a protective role in neuroinflammation, due to their ability to enable synaptic connectivity even in pathological situations (Marques et al., 2018; Wallace & Giusti, 2015). Neuroinflammation can also be moderated by Omega-3 fatty acids found in fish, among other food items (Calder, 2013). They are related to functional connectivity in the hippocampus, which is why they can improve memory (Huhn et al., 2015). Moreover, Omega-3 fatty acids could be used to treat neurological diseases like Parkinson's and Alzheimer's because they help reduce inflammation (Avallone et al., 2019).

The Mediterranean diet (MD) is considered by many to be a very attractive diet, due to being rich in important nutrients like fresh fruits, fish, seeds, nuts and vegetables (Chen et al., 2018; Riolo et al., 2022). The MD diet may play a protective role in cognitive decline, especially in older adults (Allcock et al., 2022; Corbo et al., 2023; Petersson & Philippou, 2016). Furthermore, adherence to the MD reduces the risk of mild cognitive impairment progressing into Alzheimer’s disease, as well as decreasing the risk of having the illness develop at all (Féart et al., 2010; García-Casares et al., 2021).

Another important factor to take into consideration while discussing diet patterns and cognition, is meat consumption. On one hand, some studies reported that meat consumption may have a negative effect on cognitive function, with some studies even linking it to the formation of neurodegenerative disorders, such as Alzheimer’s disease (Hashemi et al., 2023; Katonova et al., 2022; Scarmeas et al., 2018; van den Brink et al., 2019). On the other hand, Zhang et al. (2020) in their meta-analysis suggested that meat no influence on the cognition at all (H. Zhang et al., 2020). Other studies showed that meat may have protective properties on cognitive functioning (Han & Jia, 2022). This is most likely due to the type of meat that is consumed. While red meat is considered to be related to worse cognitive functioning, white meat, such as rabbit or poultry, could be related to better cognition in older age (Bramorska et al., 2021). According to Dalile et al., (2022), consumption of red meat as an older adult is associated to cognitive decline, but may offer some protection in specific domains of cognition (Dalile et al., 2022). Ylilauri et al., (2022) showed that the higher intake of processed red meat was related to worse verbal and visual memory, while higher intake of unprocessed red meat was linked to better general cognitive performance (Ylilauri et al., 2022). Consumption of meat and meat products provides a supply of important nutrients including proteins, iron and vitamins, whereas the processed meat is associated with increased risks of dementia (Giromini & Givens, 2022). This may be due to processed meat containing high amounts of saturated fat, which is known to cause inflammation in the brain (Arruda et al., 2011).

Food plays an important role in mitigating and initializing inflammation, because of the gut microbiota (Lobionda et al., 2019). Depending on the dietary pattern we consume, our gut microbiome will consist of different strains of bacteria. Lactic acid bacteria (for instance, various bacteria from the lactobacillus strain, *Streptococcus*, *Lactococcus*) may be found in fermented food products, such as kefir, certain types of cheese or sourdough bread (Borriello et al., 2003; Piwowarek et al., 2018). Similarly, bacteria of the *Bifidobacterium* genus often exists in yogurt, commercially fermented milk and sauerkraut (Fijan, 2014; Kok & Hutkins, 2018). It not only produces lactic acids which are beneficial for human health, but can also lower cholesterol levels (Gilliland, 1990; Kumar et al., 2022). Diet and dietary habits have been suggested in the literature as means of mitigating the negative effects of aging and stress on brain function and mental health.

1.2 Aims of the study

The purpose of this study was to examine the relationship between food consumption and cognitive performance and to determine whether the diet may help reduce the effects of aging on cognition. Aging is associated with a decline in cognitive performance and an increase of inflammatory response in the organism. However, findings presented in the review by Spencer et al. (2017) reported that eating certain food (like fish with its high levels of omega-3 PUFA) can help prevent negative, age-related changes in metabolism, and eating other types of food (like red meat with its high levels of saturated fat) may actually cause or increase inflammation.

The following hypothesis was formulated:

1. High consumption of unhealthy food products would result in a decrease in the performance on cognitive tasks, especially in the memory aspect.

As a following research question, it was considered whether healthy food may reduce the negative effects of aging on cognition while unhealthy food increases them.

The first study findings was published in the journal *Nutrients* (Bramorska et al., 2021).

1.3. Methods

1.3.1. Participants

Participants were recruited by the Ariadna Nationwide Research Panel (NRP) in Poland. Volunteers received research points that they could use for rewards. All participants gave their informed consent prior to participation. Informed consent was given in accordance with the Declaration of Helsinki. The design of the study, along with description of the research procedures, was approved by the SWPS University Research Ethics Committee (no 41/2019).

All participants met the following qualifications for inclusion in the study: 1. age between 20 and 55 years old, 2. normal or corrected-to-normal visual acuity, 3. normal hearing, 4. no history of neurological or psychiatric disorders, 5. no injuries, including no previous head trauma, 6. no previous head or neck surgery and no brain tumors, 7. no use of medications known to affect cognition. The study included 202 participants (101 females and 101 males).

1.3.2. Procedure

Data was collected over a 12-week period from September to October 2019. The total time commitment for this survey was 60 minutes, split evenly between two 30-minute sessions completed online. The second part was completed within a week of finishing the first as shown in Figure 1.

The first part includes a personal questionnaire and one cognitive task (Multitasking task “SynWin”) (Elsmore, 1994). The second part included two dietary questionnaires: the Food Frequency Questionnaire (FFQ questionnaire) (Jeżewska-Zychowicz et al., 2014), the Dietary Fat and Free Sugar Short Questionnaire (DFS) (Francis & Stevenson, 2013b), the Fatigue Assessment Scale (FAS), and the NEO-Five Factor Inventory (NEO-FFI) personality scale (Costa & Mccrae, 1992). However, the NEO-FFI and DFS questionnaires were not included in the analysis.

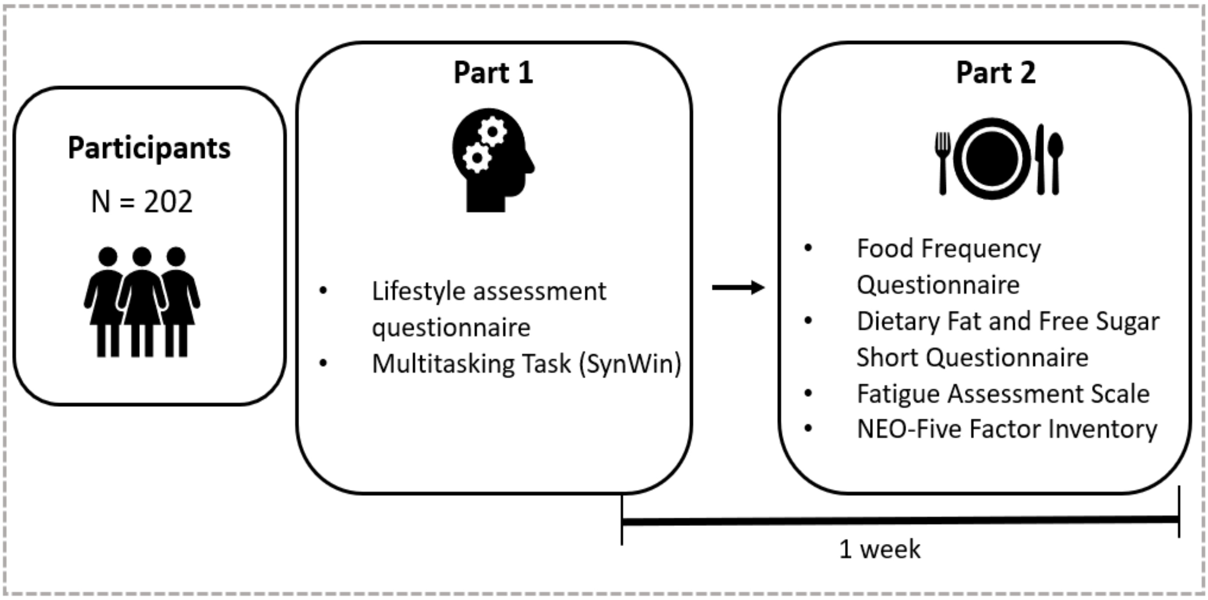


Figure 1. Study design: two parts of the study were completed within a week; 1. the first included lifestyle-related questionnaire and cognitive task; 2. the second included diet-related questionnaires, Fatigue Assessment Scale and NEO-Five Factor Inventory.

1.3.3. Lifestyle and health-related factors

Personal Questionnaire

Thirty five questions about daily activities, personal information, and the participant's health over the previous seven days were included in the personal questionnaire. As part of the analysis, BMI index was calculated (body mass divided by the square of body height) using the participants' height and weight along with their age (continuous), employment (nominal level), education (nominal level), health (1-10 range scale), and other variables.

Fatigue Assessment Scale

Fatigue was measured using the Fatigue Assessment Scale (FAS) (Michielsen et al., 2003). The scale, related to both physical and mental fatigue, had ten items with a 1–5 rating scale, where 5 was an answer “always” and 1 was an answer “never”. Two items had the scale in reverse order. The total score ranged from 10 to 50 and score more than 22 indicated substanitial fatigue and scores above 35 indicated extreme fatigue.

1.3.4. Dietary assessment

Food Frequency Questionnaire

The Food Frequency Questionnaire (FFQ) (Jeżewska-Zychowicz et al., 2014) was used to assess the composition and quality of the participants' diets within the last year. The Food Frequency Questionnaire (FFQ) is a 111-item questionnaire intended to ask about the lifestyle, diet, and specific dietary habits.

The FFQ provided for an assessment of food consumption over the course of a year, contained questions about the frequency and quantity of 165 food groups. It included two diet quality assessment indicators: (1) the pro-healthy index, which consisted of ten food groups with beneficial effects on health like fresh cheeses, fruits, vegetables or fish, and (2) the non-healthy index, which was calculated from 14 items containing food product categories that negatively impact health, for instance, fast food, soft drinks, fried food, confectionery. The FFQ manual guide was used to compute both indexes. The scores ranged from 0 to 100 and were calculated by adding the frequency of specific food consumption. The higher the index of diet value, the greater the concentration of qualities that are beneficial or harmful to human health. The Food Frequency Questionnaire (FFQ) was validated for the Polish population by Wadolowska (2005) (Wadolowska, 2005).

1.3.5. Cognitive assessment

Multitasking task (SynWin)

The SynWin task was used to assess multitasking abilities, with each task focusing on one particular cognitive function: memory, arithmetic, visual and auditory monitoring. SynWin is a multitasking simulation task that consists of four subtasks. Within three blocks, all subtasks were shown simultaneously (Figure 2). Each subtask required a different cognitive process. The SynWin task consisted of a practice section and three separate 300-second segments. Depending on how participants performed on the task, they would either gain or lose points.

Memory searching involved looking for a set of six randomly selected letters that were shown for five seconds before being removed. Then, every 10 seconds, a single letter was displayed, and the participant was asked whether or not this letter was included in the previously presented list. This subtask included the option "Retrieve List" to re-display the first set of letters, but at a cost of 10 points. The maximum number of points for that subtask in each block was 300.

The arithmetic subtask required adding two three-digit numbers and calculating the final score using the "+" and "-" buttons. The final score in each block was determined by the participant's ability.

The visual monitoring subtask consisted of a horizontal scale with a triangle pointer in the middle of the scale. The pointer skewed to the extremes of the scale, moving to the right or left. Before the pointer reached the end of the scale, participants had to press the reset button. The closer the pointer was located to the edge of the scale, the more points the participant earned, but reaching the end of the scale costed 10 points. The pointer returned to the scale's center after clicking the "Reset" button. A single block was limited to 150 points.

Auditory monitoring: one high-pitched or low-pitched sound was heard every 5 seconds during the task. If the participant heard a high-pitched sound, the "High-pitched sound" was supposed to be pressed. Each block could have a maximum of 300 points.

The overall SynWin score was the sum of all subtasks within three blocks interpreted as a measure of working memory.

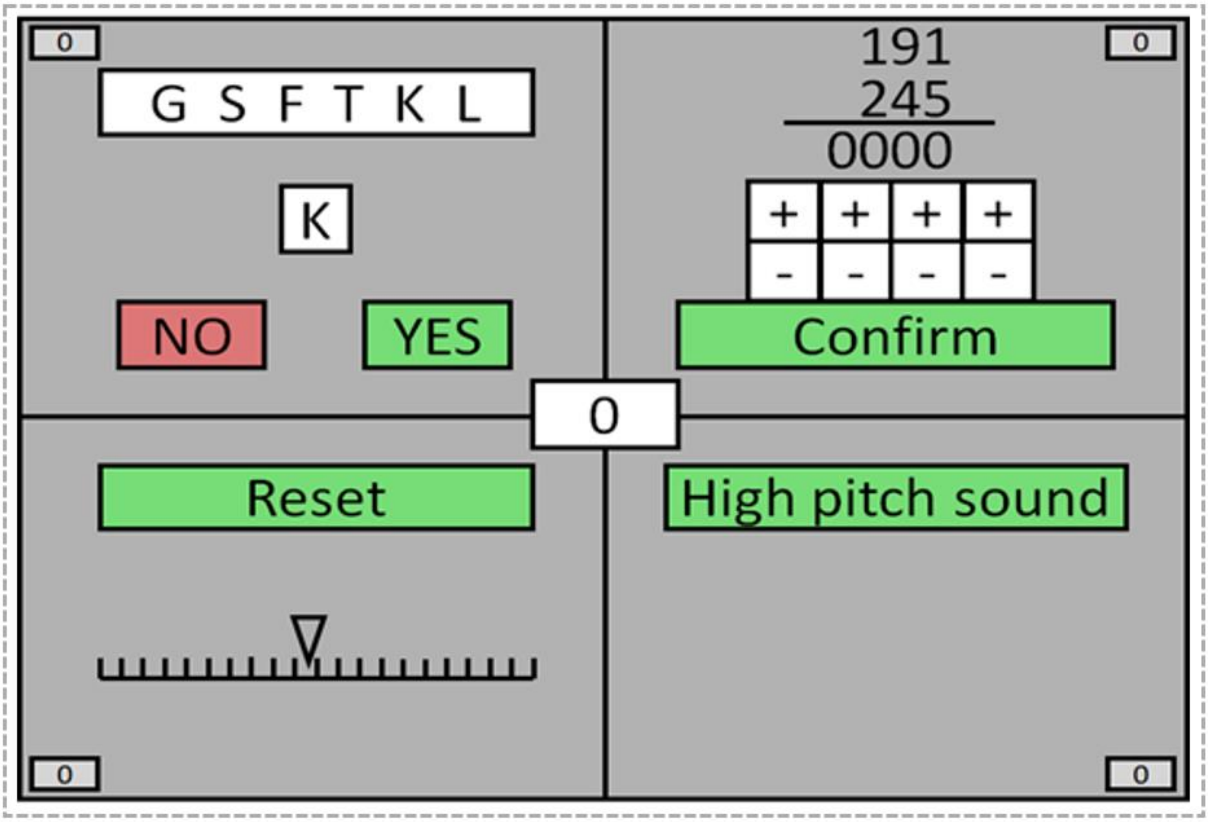


Figure 2. *Multitasking task (SynWin) contained four subtasks: memory searching (upper left corner); arithmetic task (upper right corner); visual monitoring (lower left corner); auditory monitoring (lower right corner).*

1.4 Statistical analysis

Principal component factor analysis was used for FFQ healthy and unhealthy food to obtain dietary patterns. Kaiser-Meyer-Olkin (KMO) sample adequacy and Bartlett test statistics were used to assess the correlation matrix's suitability for factor analysis. Varimax rotation with Kaiser normalization was used to extract the rotation matrix.

Pearson's correlation was used to analyze the relationship between factors describing healthy and unhealthy food consumption patterns. A stepwise regression analysis was performed to test the hypothesis that food consumption patterns affect cognitive performance. The dependent variable was cognitive task performance, and the predictors were age, food consumption patterns, and their interactions. Homoscedasticity, normality of errors, and no multicollinearity between predictors were ensured in the analysis. Because cognitive functions decline with age, the "age" variable was examined separately from the other predictors and their interaction terms. The next step of analysis proceeded with a backward selection method to assess the optimal combination of predictors. The main effects of predictors and interaction terms were examined and, if not significant, were removed from a model. To explain the interaction effects, I divided the participants into two groups based on age (those under the age of 35 (n = 102) and those above the age of 36 (n = 79)) and did separate regression models for each group.

All analyses and data preparation were conducted in the IBM SPSS Statistical Package for the Social Sciences (SPSS) version 25.

1.5 Results

1.5.1 Participants characteristics

The study recruited 204 participants, however 2 of them did not fill out all the questionnaires and were excluded from the analysis. Furthermore, participants who scored more than three standard deviations from the sample mean in BMI and the Multitasking task scores were excluded from further analysis. From the 202 participants (101 men and 101 women), the analysis involved 181 participants (Table 1).

The participants were split into age groups (people aged less than 35 years old (n = 102) and above 36 years old (n = 79), because Cole et al. 2019 showed cognitive decline after the age of 35 (Cole et al., 2019). Chi-squared test on contingency tables and independent sample Student t-test with the division of participants were performed to check health-related factors between age groups.

The study population was not dominated by any particular sex group, and the majority of participants (83.5%) were employed and had a higher education (60.8%). The age groups did not differ in sex, occupation, education, fatigue score (FAS), dietary knowledge, or dietary health indexes (FFQ). The older age group had greater BMI and lower health index and sleep quality over the week.

Table 1. Participant characteristics, descriptive statistics, and test differences for: I. all participants, II. each age group.

Characteristics	**I. All (*n* = 181)** Number/Mean (SD)	**II. Age Group ≤ 35 (*n* = 102)** Number/Mean (SD)	**II. Age Group ≥ 36 (*n* = 79)** Number/Mean (SD)	**II. Test Differences for Age Groups**
Sex	♂ 92; ♀ 89	♂ 46; ♀ 56	♂ 46; ♀ 33	X^2: 3.071
Age	35.5 (9.2)	28.7 (4.3)	44.2 (5.8)	t: −20.061 ***
Employment	83.50%	82.4%	84.8%	X^2: 0.194
Education				X^2: 0.858

Characteristics	**I. All** **(*n* = 181)** Number/Mean (SD)	**II. Age Group ≤ 35** **(*n* = 102)** Number/Mean (SD)	**II. Age Group ≥ 36** **(*n* = 79)** Number/Mean (SD)	**II. Test Differences for Age Groups**
secondary	38.1%	35.3%	41.8%	
vocational	1.1%	1%	1.3%	
higher	60.8%	63.7%	57%	
Health	7.2 (1.7)	7.5 (1.6)	6.9 (1.7)	t: 2.235 *
BMI	24.7 (4.9)	23.1 (4.0)	26.9 (5.2)	t: −5.534 ***
FAS score	22.83 (7.3)	23.1 (7.3)	22.4 (7.2)	t: 0.638
Dietary knowledge	12.4 (4.5)	11.9 (4.4)	13.0 (4.5)	t: −1.660
Pro-Healthy Diet Index	20.1 (10.0)	20.0 (10.5)	20.2 (9.4)	t: −0.140
Non-Healthy Diet Index	16.3 (8.2)	16.9 (8.7)	15.6 (7.5)	t: 1.08
Smoking	22.7%	19.6%	26.6%	X^2: 1.236
Sleeping quality (weeks):				X^2: 5.919 *
7–8 h	61.9%	69.6%	51.9%	
<7 h or >8 h	38.1%	30.4%	48.1%	
Sleep quality (weekends):				X^2: 0.297
7–8 h	63.0%	64.7%	60.8%	
<7 h or >8 h	37.0%	35.3%	39.2%	
Physical activity				X^2:2.792
sedentary or light	59.1%	63.7%	53.2%	
medium active	37.6%	32.4%	44.3%	
vigorously active	3.3%	3.9%	2.5%	
Diet type				X^2: 0.002
omnivore	95%	95.1%	94.9%	
vegan	5%	4.9%	5.1%	

SD = standard deviation; BMI = Body Mass Index; FAS = Fatigue Assessment Scale; * *p* value < 0.05, *** *p* value < 0.001.

1.5.2 Food consumption patterns

For pro-healthy food product (KMO: 0.6; Bartlett test: chi-square: 306.4, p value < 0.001), the four factors together explained 63% of the cumulative variance in the extracted components: Fruits and vegetables, Fermented dairy, Legume vegetables and wholegrains and White meat and Fish. Scores loaded each component of pro-healthy food are included in Table 2.

Table 2. Component matrix of pro-healthy food.

	Fruit and Vegetables;	**Fermented Dairy, Cottages;**	**Legumes, Whole grain**	**White Meat and Fish**
whole meal bread	0.536	0.073	0.155	0.017
whole grain cereal	0.163	0.373	0.623	−0.046
milk	0.387	0.456	−0.185	0.208
fermented dairy	0.091	0.845	0.02	0.005
fresh stretched curd cheeses	0.016	0.687	0.404	0.12
white meat	0.040	0.182	−0.130	0.837
fish	0.072	−0.061	0.443	0.734
legume vegetables	0.128	−0.038	0.854	0.099
fruits	0.850	0.083	0.037	0.048
vegetables	0.815	0.052	0.095	0.025

Similarly, for non-healthy food (KMO: 0.7; Bartlett test: chi-square: 445.7, p value < 0.001) the four factors together explained 54% of the cumulative variance of the extracted components: High-Carbohydrates and High-Fat Food (HCHF food) component, Fast Food, Meat and Animal fat, Refined grains and cheeses. Scores loaded each component of not-healthy food are included in Table 3.

Table 3. Component matrix of non-healthy food.

	HCHF food	**Fast Food, High-Sugar Drinks**	**Meat and Animal Fat**	**Refined Grains, Cheeses;**
white flour baked food	0.742	0.060	−0.190	0.076
refined grains	0.043	0.057	−0.014	0.726
fast food	0.022	0.631	0.265	0.282
fried food	0.647	0.235	0.025	0.167
butter	0.576	−0.202	0.116	0.172
lard	−0.049	0.073	0.762	0.281
moldy, processed, semi-hard cheeses	0.318	−0.029	0.145	0.515
lunch meat	0.631	−0.033	0.343	−0.170
red meat	0.395	−0.008	0.603	−0.187
confectionery	0.434	0.350	−0.158	0.285
canned meat	−0.002	0.295	0.734	−0.022
carbonated soft drinks	0.143	0.774	0.054	−0.054
energy drinks	−0.279	0.578	0.451	0.029
alcohol	0.026	0.595	0.039	−0.479

Relationships between healthy and unhealthy food consumption patterns were examined using Pearson's correlation (Table 4). Fruits and vegetables were negatively related to Fast food ($p < 0.01$), while Fermented dairy and cottage cheese were positively related to Refined grains and cheeses. Legume vegetables and wholegrains negatively associated with HCHF food and correlated positively with Meat and animal fat and Refined grains and cheeses (both $p < 0.01$). White meat and fish consumption component was positively related to Meat and animal fat and HCHF food components ($p < 0.01$).

Table 4. Pearson correlations among healthy and non-healthy factors describing food consumption patterns from the FFQ questionnaire.

	HCHF Food	**Fast Food, High-Sugar Drinks**	**Meat and Animal Fat**	**Refined Grains, Cheeses**
Fruit and vegetables;	0.06	−0.193**	−0.08	0.101
Fermented dairy, cottages;	0.105	−0.091	−0.041	0.203**
Legume vegetables, whole grain	−0.315**	0.015	0.306**	0.218**
White meat and fish	0.283**	0.073	0.379**	−0.119

** *p* value < 0.01.

2.5.3 Food consumption patterns and Multitasking task performance

Linear regressions were calculated to predict the Multitasking task performance based on age and eight components of food consumption patterns, including their interaction effects. For the overall task score and each subtask score, age was entered as the only factor in the first step; eight components of consumption patterns were included in the second step; and in the third step their interactions with age was introduced. The age score predictor was standardized before the analysis, while consumption patterns were components of the factor analysis. Effects that were not significant were subsequently excluded from the model with the lowest Akaike Information Criterion (AIC). Significant models were found for the overall task score and the memory search subtask. The next step was to look at single interactions and the effects that were found to be important. Participants were divided into age groups (less than 35 (n = 102) and over 36 (n = 79) to explain the interaction impact between age and food consumption patterns. Regression analysis was performed for each age group separately using food consumption patterns as predictors.

Overall Multitasking task score

Using stepwise regression with backward selection method, the final model included age ($\beta = -0.404$) and the interactions of age with the HCHF food component ($\beta = -0.15$) and age with the Meat and animal fat component ($\beta = -0.161$) to predict cognitive functioning performance based on the overall Multitasking task score. The final model with the age predictor and the interaction terms was statistically significant ($F(3, 177) = 15.538$, $p < 0.001$) with an R^2 of 0.208 and AIC of 1825.6 (Table 5).

Table 5. Summary of linear stepwise regression analysis for various consumption patterns predicting SynWin multitasking performance in the group of all participants (*n* = 181).

Stepwise Regression on SynWin Multitasking Performance

Variables	**B**	**SE**	**β**	**t**	***p***	**R^2**	**ΔR^2**	**F Statistic**	**AIC**
Step 1					0.000	0.155	-	32.839	1833.5
Age	−67.087	11.707	−0.394	−5.731	0.000				
Step 2					0.457	0.162	0.007	0.787	1835.9
Age	−66.730	11.736	−0.392	−5.686	0.000				
HCHF food	10.498	11.722	0.062	0.896	0.372				
Meat and animal fat	−10.308	11.735	−0.060	−0.878	0.381				
Step 3					0.003	0.217	0.054	6.065	1827.7
Age	−68.677	11.461	−0.403	−5.992	0.000				
HCHF food	9.44	11.512	0.055	0.82	0.413				

Meat and animal fat	−12.668	11.52	−0.074	−1.100	0.273				
Age × HCHF food	−24.734	12.209	−0.138	−2.026	0.044				
Age × Meat and animal fat	−34.386	13.442	−0.175	−2.558	0.011				

Final model on SynWin multitasking performance

Variables	**B**	**SE**	**β**	**t**	***p***	**R^2**	**ΔR^2**	**F statistic**	**AIC**
Final model					0.000	0.208	-	15.538	1825.6
Age	−68.913	11.446	−0.404	−6.021	0.000				
Age × HCHF food	−26.852	12.081	−0.150	−2.223	0.028				
Age × Meat and animal fat	−31.740	13.293	−0.161	−2.388	0.018				

ΔR^2 = difference in the proportion of variance explained in reference to the step 1 regression; B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient; AIC = Akaike Information Criterion. The dependent variable was the total SynWin score. HCHF = High-carbohydrates and high-fat.

The interaction plot showed that as HCHF food intake increased in the older age group, the Multitasking performance decreased, yet in the younger age group, performance on task increased (Figure 3A). Performance on task decreased significantly as the frequency of Meat and animal fat consumption increased in the older age group (Figure 3B).

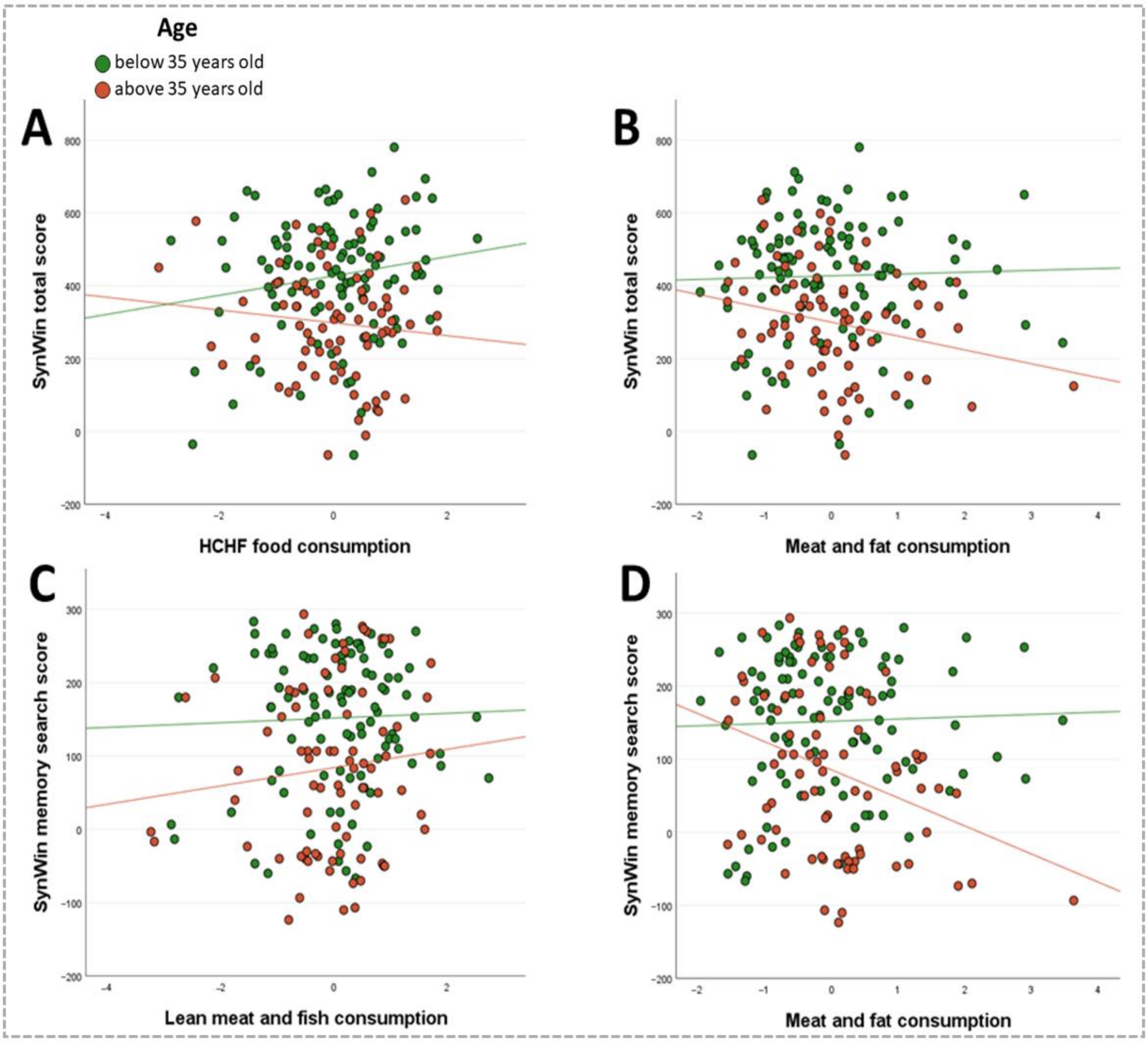


Figure 3. (A). Linear regression analyses of the associations between younger and older age groups and SynWin total score predicted by high-carbohydrates and high-fat (HCHF) consumption. (B). Linear regression analyses of the associations between younger and older age groups and SynWin total score predicted by meat and animal fat consumption. (C). Linear regression analyses of the associations between younger and older age groups and SynWin total score predicted by white meat and fish consumption. (D). Linear regression analyses of the associations between younger and older age groups and SynWin memory search score predicted by meat and animal fat consumption.

In terms of age group division, regression analysis was performed for each subgroup using HCHF food and Meat and animal fat components as predictors. Both models did not show a significant relationship between the amount of HCHF food frequency consumption and the performance of a cognitive task with age (Table 6). The model for the group above 35 years old (F(2, 76) = 2.595, p = 0.081) showed a tendency that higher scores of the Meat and animal fat components correlated with Multitasking task performance decreasing with age (β = −0.228) (Table 6). Performance on task decreased significantly as the frequency of Meat and animal fat consumption increased in the older age group (Figure 3B). The model for the group below 35 years old was not significant.

Table 6. Explanations of the interaction effects (age x HCHF food and age x meat and fat age) showing a simple effect for younger and older age groups on SynWin multitasking performance predicted by the frequency of HCHF food consumption and meat and animal fat frequency consumption.

Variables	**B**	**SE**	**β**	**t**	***p***	**R^2**	**F Statistic**
Age below 35					0.22	0.03	1.535
HCHF food	26.589	15.441	0.170	1.722	0.088		
Meat and animal fat	5.624	15.308	0.036	0.367	0.714		
Age above 35					0.081	0.064	2.595
HCHF food	−16.063	17.892	−0.100	−0.898	0.372		
Meat and animal fat	−37.382	18.187	−0.228	−2.055	0.043		

B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient. HCHF = High-carbohydrates and high-fat. The dependent variable was the total SynWin score.

Memory search subtask

Using stepwise regression with backward selection, the final model for memory search included age (β = −0.321), the white meat and fish component (β = 0.157), the meat and animal fat component (β = −0.204), and an interaction between age and the white meat and fish (β = 0.136, however, not significant) and the meat and animal fat (β = −0.237) components. The final model was statistically significant (F(5, 175) = 7.301, $p < 0.001$) with an R^2 of 0.173 and the lowest AIC of 1669.8 (Table 7).

Table 7. Summary of linear stepwise regression analysis for various consumption patterns predicting the impact on SynWin memory search performance for all participants (*n* = 181).

Stepwise Regression on SynWin Memory Search Score

Variables	**B**	**SE**	**β**	**t**	***p***	**R^2**	**ΔR^2**	**F statistic**	**AIC**
Step 1					0.000	0.102	-	20.229	1676.7
Age	−34.153	7.593	−0.319	−4.498	0.000				
Step 2					0.125	0.130	0.029	1.939	1676.9
Age	−33.040	7.557	−0.308	−4.372	0.000				
White meat and fish	12.411	8.565	0.116	1.449	0.149				
HCHF food	4.671	7.916	0.044	0.590	0.556				
Meat and animal fat	−16.743	8.220	−0.156	−2.037	0.043				
Step 3					0.007	0.189	0.058	4.152	1670.3
Age	−34.215	7.389	−0.319	−4.630	0.000				
White meat and fish	14.273	8.387	0.133	1.702	0.091				
HCHF food	4.948	7.764	0.046	0.637	0.525				
Meat and animal fat	−20.356	8.146	−0.190	−2.499	0.013				
Age × White meat and fish	16.551	7.683	0.171	2.154	0.033				

Age × HCHF food	−13.538	8.095	−0.120	−1.672	0.096
Age × Meat and animal fat	−29.585	9.676	−0.239	−3.058	0.003

Final model on SynWin memory search score

Variables	**B**	**SE**	**β**	**t**	***p***	**R^2**	**ΔR^2**	**F statistic**	**AIC**
Final model					0.000	0.173	-	7.301	1669.8
Age	−34.399	7.412	−0.321	−4.641	0.000				
White meat and fish	16.831	8.031	0.157	2.096	0.038				
Meat and animal fat	−21.854	8.117	−0.204	−2.692	0.008				
Age × White meat and fish	13.217	7.491	0.136	1.765	0.079				
Age × Meat and animal fat	−29.290	9.699	−0.237	−3.020	0.003				

ΔR^2 = difference in the proportion of variance explained; B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient; AIC = Akaike Information Criterion. The dependent variable was the memory search SynWin score. HCHF = High-carbohydrates and high-fat.

The models fitted among age groups division showed a relationship between the older age group and the performance of a memory search task with various meat patterns ($F(2, 76) = 7.453$, $p < 0.001$) (Table 8). The model showed that for higher scores on meat and animal fat ($\beta = -0.428$) consumption in the older age group, the SynWin memory search task score decreased (Figure 3D). Meanwhile, with higher scores on the white meat and fish ($\beta = 0.283$)

component in the older age group, the SynWin memory search task score increased (Figure 3C). The model for the group below 35 years old was not significant.

Table 8. Explanations of the interaction effects (age × white meat and fish and age × meat and animal fat) showing a simple effect for younger and older age groups on SynWin memory search score predicted by the frequency of white meat and fish consumption and meat and animal fat frequency consumption.

Variables	**B**	**SE**	**β**	**t**	***p***	**R^2**	**F Statistic**
Age below 35					0.913		
White meat and fish	2.322	9.738	0.026	0.238	0.812	0.002	0.091
Meat and animal fat	2.281	9.360	0.026	0.244	0.808		
Age above 35					0.001		
White meat and fish	32.732	13.303	0.283	2.461	0.016	0.164	7.453
Meat and animal fat	−52.614	14.135	−0.428	−3.722	0.000		

B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient. The dependent variable was the SynWin memory search score.

1.6 Summary

The purpose of the study was to see how the diet rich in added sugars and saturated fat affects cognitive performance in a group of 202 healthy people and to check whether the dietary patterns' influence on cognition changes with age. Stepwise regression analysis demonstrated that cognitive task performance decreased with age using age and food consumption patterns as predictors and cognitive task performance as the dependent variable. However, the effect of age on cognitive performance is mitigated by the frequency with which different types of food are consumed (healthy versus unhealthy).

The most intriguing finding is that the memory sub-task performance is differentially affected by the consumption of the different types of meat, white or red in the group of older participants. Eating more white meat and fish was associated to better performance on the memory sub-task, while eating more red meat and animal fat was related to worse performance. Meat, and particularly red meat, has yet to be fully understood as it relates to how the brain is functioning. Iron deficiency in childhood has been linked to impaired hippocampus-dependent memory (Cavallucci et al., 2020), and red meat is a good source of this mineral (Jackson et al., 2016). Zupo et al. (2021) found that a diet that avoided red meat was associated with cognitive impairment and seemed to have beneficial effects on cognition (Zupo et al., 2022).

Animal fat, however, has been also associated with the inflammatory processes in the body (Milanski et al., 2009). While aging is related with an increase in inflammatory markers, it may also have an impact on mental health (Lucassen et al., 2010). Greater red meat consumption in humans have been linked to slower attention, concentration, and information processing speed in the elderly, but has no effect on the rate of cognitive decline (Granic et al., 2016). It may possibly be related to the findings, which suggest that frequent red meat and animal fat consumption can reduce cognitive performance with age.

Diet is a significant factor in determining the composition and diversity of the gut microbiota (Turnbaugh et al., 2009). A diverse and well-functioning gut microbiota is essential for health because it provides the body with necessary nutrients and eliminates pathogenic microorganisms that would otherwise cause illness (Forsythe et al., 2016). In addition, certain gut microorganisms affect brain function by generating neurochemicals from dietary substrates or by reacting to neuroactive food components (Lyte, 2014). The gut microbiota may play a role in the association between specific dietary products and cognitive performance.

2. Study 2. Gut microbiota and human cognitive functioning: a correlational approach

2.1. How does gut microbiome influence cognition?

Gut microbiota is a component of the gut-brain axis, the unconscious system that regulates behavior. Literature describes the potential impact of the gut microbiome on broad aspects of human health, including emotional behavior and cognition, via the gut-brain axis (Cryan et al., 2019; Dinan et al., 2015; Dinan & Cryan, 2012; Forsythe et al., 2016; Sarkar et al., 2018). Bidirectional communication along the gut-brain axis is a critical component of the microbiota and host interaction in accessing gut-brain signaling pathways to influence host brain and behavior (Grenham et al., 2011).

The autonomic nervous system, the endocrine system, and the immune system all play a role in mediating communication between the intestinal microbiota and the central nervous system (CNS) (Dinan et al., 2015). The vagus nerve acts as a connection between the digestive system and the brain. The afferent and efferent fibers of the tenth cranial nerve convey information between the visceral organs and the brain (Cryan et al., 2019). Due to its position as the first brain region to receive a signal from the gut via the vagus nerve, the nucleus tractus solitarius plays a crucial role in this exchange of information (Cryan et al., 2019). Modifying vagus nerve activity is one way in which microbiota can affect brain function (Rogers et al., 2016). Sarkar et al. (2016) suggest that the CNS may be affected by the production of short-chain fatty acids (SCFA) or by the regulation of intestinal hormone secretion (Sarkar et al., 2016). Gut bacteria produce neurochemical substances from substrates that are present in food, influencing brain function, for example, by regulating serotonin production (Forsythe et al., 2016). The vagus nerve, spinal nerve, and spinal cord play crucial roles in facilitating communication between the gastrointestinal (GI) tract and the CNS. Maintaining homeostasis and healthy growth are impossible without constant, bidirectional communication between the gut and the brain (Grenham et al., 2011). Probiotics have been shown to have effect on the activity of areas related to sensory sensation and emotion control (Tillisch et al., 2013) demonstrating close relationship between digestive system state and cognitive and emotional processes.

The imbalance of the microbiota in the digestive tract is called dysbiosis (Rogers et al., 2016). According to studies, food is an important factor determining diversity and functioning of the gut microbiota, and poor quality of food can contribute to inflammation and pathogenic bacteria colonization (Rogers et al., 2016; Sonali et al., 2022). Anxiety disorders have been linked to chemical substances secreted by both pathogenic and commensal (beneficial to the host) bacteria, what is more, those substances have been shown to affect limbic structures, including the amygdala (Bested et al., 2013). Because of the close bidirectional relationship between the digestive system and mental health, being stressed, anxious, or depressed can also negatively affect the digestive system. Tillisch et al. (2013) found a strong correlation between mental and emotional processes and gastrointestinal health, what was also shown with the functional magnetic resonance imaging (Tillisch et al., 2013). Serotonin and gamma-aminobutyric acid are just two examples of the neurotransmitters and neuromodulators that are synthesized by gut bacteria and then transported to the CNS (Dinan et al., 2015). Some bacteria in the gut can break down dietary fiber and carbohydrates. SCFA are a product of bacterial metabolism (Macfarlane & Macfarlane, 2003). The activity of the gut-brain axis is significantly influenced by SCFA. They influence brain function, for instance, have anti-inflammatory effects, and control the production of serotonin (Forsythe et al., 2016) and GI hormones (Sarkar et al., 2016).

The bacteria alert the brain about impaired gut function, which stimulates the hypothalamic-pituitary-adrenal (HPA) axis and cortisol secretion, both of which are necessary to suppress the immune response while increasing previously felt anxiety; long-term increases in HPA axis activity and declines in intestinal microbiota quality have been linked to traumatic stress in rats (Bailey et al., 2011). Mood regulation, as well as normal and impaired cognitive functioning (Schmitt et al., 2006), are all influenced by serotonin, a neurotransmitter whose metabolism can be disrupted by inflammation (Bercik et al., 2011). Reduced levels of brain-derived neurotrophic factor (BDNF) protein secretion, a potent modulator of synaptic plasticity, especially in the hippocampus, has been linked to cognitive dysfunction due to chronic inflammation (Gareau et al., 2011).

EEG data shows that certain probiotic strains reduce stress-related conditions by modulating the gut-brain axis and enhancing cognitive performance (A. P. Allen et al., 2016). Mental health and cognitive performance have also been shown to benefit from probiotics that interact directly with intestinal bacteria (Sarkar et al., 2016). Memory loss, a weakened working memory, and slowed learning were all observed in germ-free mice (Gareau et al., 2011). Restoring a healthy, balanced gut microbiota was necessary to bring these mice back to homeostasis after limbic system dysfunction caused them to respond less to stressful situations (Sudo et al., 2004).

Composition, structure and function of the brain are dependent on the availability of appropriate nutrients (Adan et al., 2019). Research indicates that diet and nutritional patterns also affect the improvement or deterioration of cognitive functions, and diet-related diversity of the gut microbiota may additionally affect the metabolism of the food (Hsu & Kanoski, 2014; Lyte & Cryan, 2014; Turnbaugh et al., 2006; Wu et al., 2016). Probiotics, a microorganism components that are beneficial to the health, improve mood and brain function through their interactions with gut microbiota (Bested et al., 2013; Bloemendaal et al., 2021). Probiotics and a more varied microbiota have recently been proposed as a potential treatment for cognitive decline in healthy people (Sarkar et al., 2016).

Specific gut microbiota have been linked to better cognitive performance (learning, attention, and memory) in both humans and animals. A higher proportion of *Verrucomicrobia* bacteria is positively associated with indices of memory, attention, and executive function in healthy older people, according to preliminary reports by Manderino et al. (2016). The study also found that having a higher proportion of *Firmicutes* bacteria had a significant beneficial effect on memory (Manderino et al., 2017). Higarza et al. (2023) demonstrated that rodents fed a high-fat diet had altered microbiota diversity and decreased cognitive function. However, after *Akkermansia muciniphila* administration, cognitive function as well as brain metabolism and gut microbiota improved (Higarza et al., 2023).

2.2. Aims of the study

The second stage of the doctoral research was aimed at clarifying the findings of the first study in relation to the gut microbiota. A healthy gut microbiota requires a balanced diet and nutritious foods. By metabolizing the appropriate nutrients, bacteria support the digestive system and are important in the production of hormones and neurotransmitters such as serotonin. The review of Adan et al. (2019) reported that diet and nutrition are not only critical for human physiology and body composition, but also have significant effects on mood and mental wellbeing.

The following hypotheses were formulated:

1. High consumption of unhealthy food products would result in a decrease of cognitive tasks performance, however the effect of food will vary between the omnivore diet groups and vegan diet groups owing to their distinct microbiota profiles.

2. Cognitive performance may be affected by dietary patterns; however, a healthy microbiome profile can mitigate the negative effects of harmful food.

The separate, more exploratory, research question was also formulated: whether specific gut bacteria can offer protection and mitigate the adverse effects of consuming unhealthy foods..

2.3. Methods

2.3.1 Participants

Participants were invited to study by online advertisements in Poland. All participants gave their informed consent prior to participation. Informed consent was given in accordance with the Declaration of Helsinki. The design of the study, along with a description of the research procedures, was approved by the SWPS University Research Ethics Committee (no 74/2020).

Participants reported: 1. normal or corrected-to-normal visual acuity, 2. normal hearing, 3. no history of neurological or mental diseases or traumas, including no past head trauma, head or neck surgery, or brain tumors, 4. no use of medication known to influence cognition. The study included 396 participants between the ages of 18 and 70 (339 females and 57 males).

2.3.2 Procedure

The study was conducted on-line via research platform and consisted of two parts. For the first part, data were collected from May 2020 to December 2022. For the second part, data were collected between October 2020 and April 2021. After completing the first part's questionnaires and cognitive tasks, each participant collected a fecal sample within three months. After completing the collection of fecal samples, recruitment continued for the first part of the study in order to obtain the largest sample size possible.

The first part was divided into three sections (Figure 5). Participants were instructed to complete that part within seven days of beginning the first block. After that, they kept a record of the meals that they consumed. They recorded everything they consumed throughout the day and into the night for a total of three days (two weekdays and one weekend day; the days were not consecutive).

Lifestyle assessment questionnaire was related to demographic and health-related questions. The second block contained three psychological questionnaire - the NEO-Five Factor Inventory (NEO-FFI) personality factors (Costa & Mccrae, 1992), the UMACL mood adjective checklist (UMACL) (G. Matthews et al., 1990) and the State-Trait Anxiety Inventory (STAI) (Spielberger & Sydeman, 1994); two dietary questionnaires - the Food Frequency Questionnaire (FFQ questionnaire) (Jeżewska-Zychowicz et al., 2014) and the Dietary Fat and Free Sugar – Short Questionnaire (DFS) (Francis & Stevenson, 2013b), then Fatigue Assessment Scale (FAS) (Michielsen et al., 2003), International Physical Activity Questionnaire (IPAQ) (Craig et al., 2003) and WHO Quality of Life (Skevington et al., 2004). That block was split into smaller sections of two-three questionnaires. After fulfilling all questionnaires, the participants were asked to complete two cognitive tasks - the Multitasking (SynWin) (Elsmore, 1994) and Mental Rotation Task (MRT) (Peters et al., 1995). However, FFQ, SynWin and MRT only were used in the presented analyses.

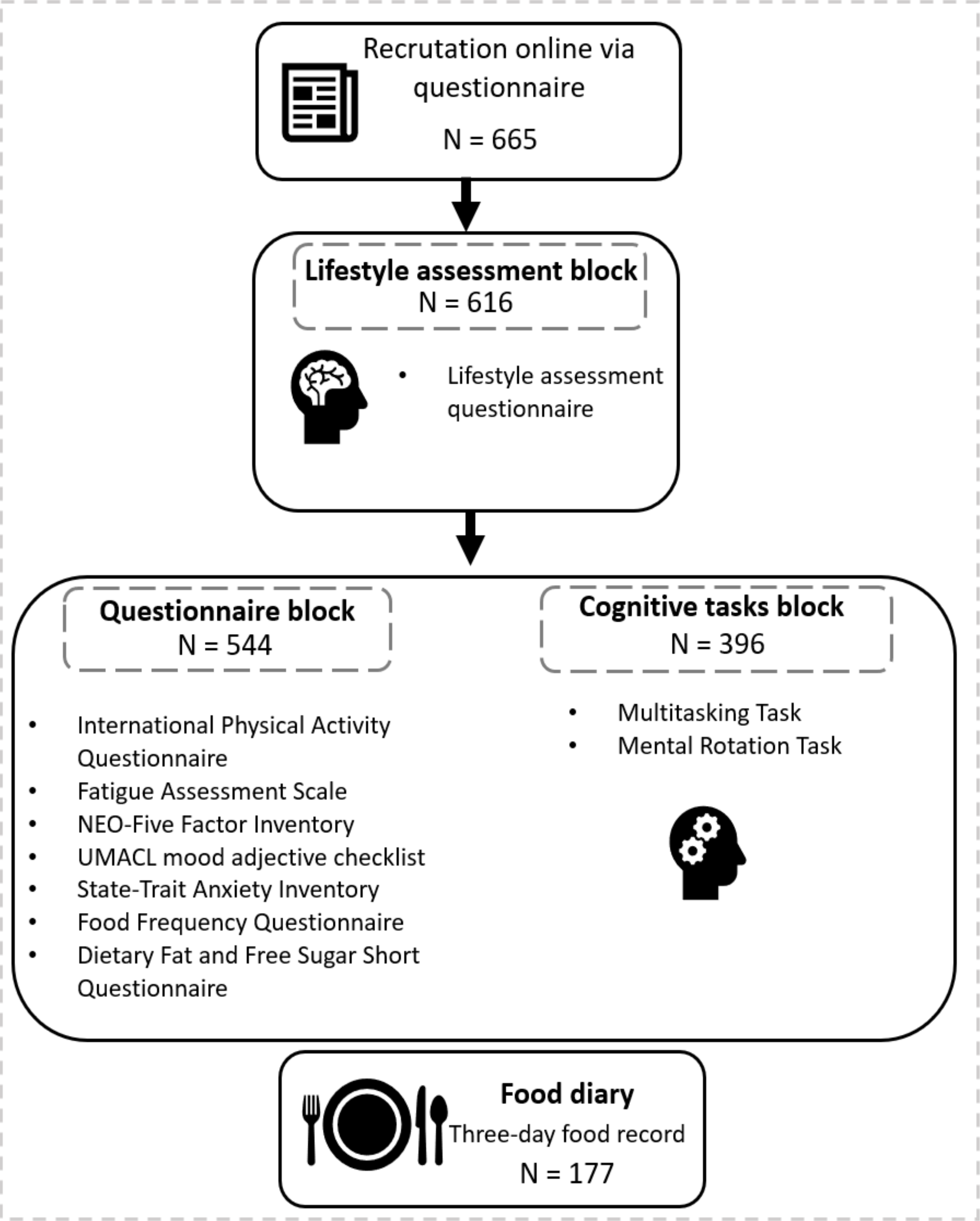


Figure 5. Study design: three blocks of varied tasks and questionnaires were completed over the course of seven days. A food diary was fullfilled for three consecutive days.

The second part consisted of online measurements and microbiota samples collection (Figure 6). Only female adults were selected to reduce heterogeneity in the sample. Those subjects were invited to participate in a more extensive set of cognitive tasks and provided a fecal sample. The selection of participants was based on the following criteria: 1) vegetarian or omnivore diet and 2) within these groups the highest and lowest quartiles of unhealthy food consumption. This selection was done to include subjects with relevant variation in dietary habits. Sixty-eight females participated in the microbiota sub-study, of which 31 vegetarians and 37 omnivores. We were unable to gather people who adhere to a strict vegan diet.

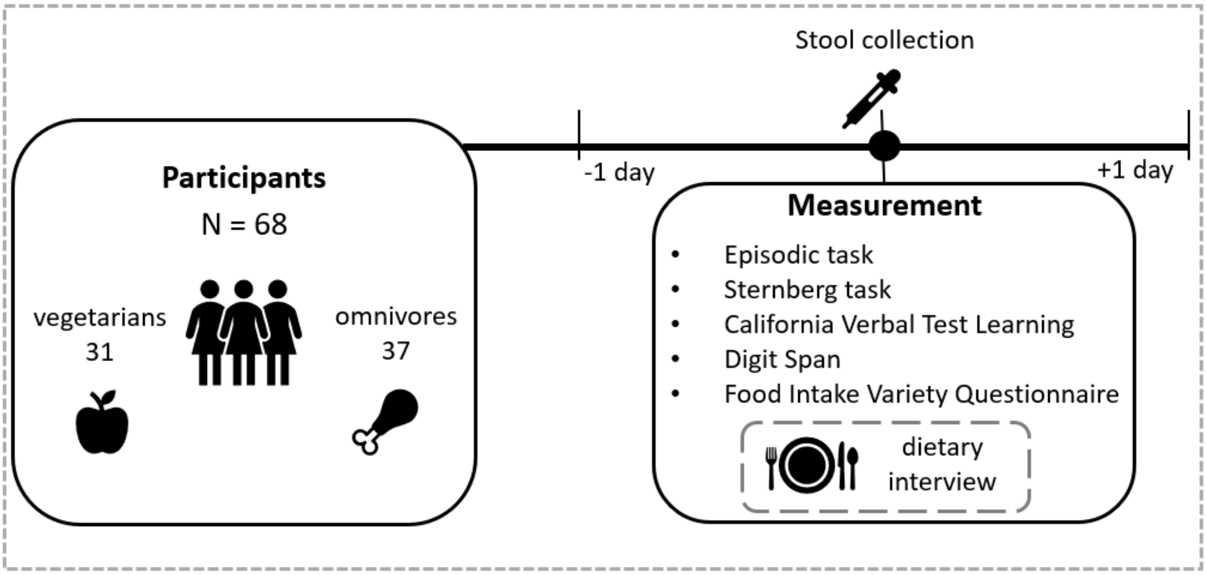


Figure 6. Sixty-eight females participated in the microbiota sub-study, of which 31 vegetarians and 37 omnivores.

Participants received a kit to collect fecal material and the online meeting took place on the same day the material was collected. Then, the fecal samples were collected by researcher within one week. The measurements were conducted online, however, the researcher was present during the whole meeting via video conferencing application. The cognitive tasks in the sub-study were the episodic memory task (Old/New), Starnberg task (Sternberg, 1966) and two paper-pencil cognitive tasks - the California Verbal Learning Test

(CVLT) (S. P. Woods et al., 2006) and the Digit Span (DS) subtest of the Wechsler Memory Scale-III (WMS-III) (Tulsky et al., 2003). The paper-pencil tasks were conducted by the researcher (participants were giving auditory responses). In the middle of CVLT (before long-delay recall of the words), a prepared dietary interview and the Food Intake Variety Questionnaire (FIVeQ) (Niedzwiedz & Wadolowska, 2008) were used for detailed dietary assessment and we also controlled the FFQ score obtained in the initial part of the study. Both computerized tasks (Old/New and Sternberg task) were performed with the Inquisit 5 Lab software.

2.3.3. Dietary assessment

Food Frequency Questionnaire

The Food Frequency Questionnaire (FFQ) (Jeżewska-Zychowicz et al., 2014) was used to obtain indicators of the quality of the participant’s diet within the last year. The questionnaire was the same one that had been used in previous research, (see page 29).

2.3.4 Cognitive assessment

Multitasking task

The SynWin task is a multitasking simulation task, the same one that had been used in the previous study (see page 30 for detailed description).

Mental Rotation Task

Mental Rotation Task was originally developed by Vandenberg and Kuse (1978) with figures created by Shepard and Metzler (1971). The Version A of MRT redrawn was used (Peters et al., 1995) with author permission. The task consists of two sets with 12 items that contain respectively a target item on the left side on the screen and four sample stimuli on the right side. Participants had to identify those two out of four sample stimuli that show the target item in a rotated version. The items were presented in two sessions, each lasting 4 minutes to solve a set of 12 items. There was a two-minute break between the two sessions. Instructions were given at beginning, followed by three training items to help participants get familiar with the task. The task is interpreted as a spatial memory ability.

California Verbal Test Learning

The CVLT consists of three lists of words: A, B, and a list of words to recognize. Lists A and B each have 16 words that are categorically connected and relate to supermarket items. Participants had to learn list A by repeating it five times immediately after the presentation, then were asked to recall it after a presentation of B list (a short delay recall). After 20 minutes, the participant attempted a long delay recall by trying to recall words from list A again. The final step involved identifying list A items from a set of 44. There are a total of 44 words on the list to recognize; this includes all of the words on list A, some words on list B, and additional distractors that meet certain criteria (such as sounding similar to words on list A). CVLT measures the ability to learn and remember verbal material.

Digit Span (DS) test from the Wechsler Memory Scale-III (WMS-III)

Participants were asked to repeat a series of numbers containing two trials. After that, they were asked to either repeat the digits in the same order in which they had heard them or in reverse. For each succeeding set, the number of digits increased. Digit Span assesses the effectiveness of cognitive functioning and information processing.

Episodic memory measurement (Old/New recognition task)

The episodic memory task had two stages: the first was a learning phase, and the second was a recognition phase, separated by at least 15 minutes. During the training session, each participant was exposed to 100 new, unseen images from one of five categories (cars, people, animals, landscapes, and food), presented in a randomized order. The same number of images were shown in each grouping. One second was spent showing each image. In order to keep their attention on the first stage, participants were asked to determine whether or not the presented images showed animals. There was at least a 15-minute break between the learning and recognition sessions, during which a distraction task (a Sternberg task) was administered to prevent rehearsal.

A total of 100 images were shown to the participants during the recognition session; 50 were completely novel, and the remaining 50 were reviewed from the learning session (the same number of images were presented for each category). Participants were asked to rate their certainty that they were familiar with the image ("old" or "new") on a 6-point scale. Participants gave their responses by clicking on buttons on a computer keyboard. There was no time limit on providing an answer. One hundred and fifty pictures were selected to be used in the current study from Wikimedia Commons under a CreativeCommons license.

Sternberg task

Participants performed a computerized version of Sternberg's paradigm (Sternberg, 1966). Each trial consisted of 2 to 6 white digits presented on a black screen in a sequence (1500 ms each). After the maintenance period (1000 ms after the last digit) a yellow digit (target) appeared and participants had to indicate whether the displayed sequence contained this digit or not (by pressing the adequate button). Task sessions were divided into equally distributed positive ("in" – probe present in the memory sequence) and negative ("out" – probe not present in the memory sequence) attempts. There were 120 experimental trials in total, preceded by 15 trials of the training.

2.3.5. Microbiota-related procedures

Fecal sample collection

A total of 68 participants were tested. For the reason of covid-19 epidemiological threat, samples from 54 patients were tested first and after three months - 14 more patients were tested. Fecal samples were self-collected by participants at home using commercially available, validated protocol by OMNIgene®•GUT kit (DNAGenotek, Ottawa, CA).

Bacterial DNA isolation and sequencing

All samples collected by this method were kept at room temperature for 50 days. The total amount of sample used (from the OMNIgene•GUT kit) for DNA extraction was 0.25 mL containing approximately 50 mg feces and 200 µL stabilizing liquid. DNA purification was performed with a customized kit (QIAamp®PowerFecal®ProDNA Kit) according to the manufacturer's instructions (Qiagen, Hilden, Germany). PCR amplification of the 16S rRNA genes was performed with primers containing universal primers amplifying the V3-V4 variable region:(Il-16Sv34F CCTACGGGNGGCWGCAG) and Il-16Sv34R GACTACHVGGGTATCTAATCC.

The PCR negative sample was included to assess the contamination introduced during this step. We also used a positive control - ZymoBIOMICS Microbial Community Standards, commercially available standard for microbiomics and metagenomics studies (Zymo mock; Zymo Research, Irvine, CA, USA). The microbial standard is a well-defined, accurately characterized mock community consisting of Gram-negative and Gram-positive bacteria. In addition, the primers contained Illumina tags and barcodes. Samples were barcoded with a unique combination of forward and reverse indexes allowing for simultaneous processing of multiple samples. Sequencing was performed in a pair-end modality on the Illumina MiSec platform producing 2 x 250 bp pair-end sequences (Illumina, San Diego, California, USA).

The preceding paragraph was written by Szymon Wardak and Damian Loska, because microbiome sample processing was performed by Centrum Medyczne MedGen, Genomed S.A., A&A Biotechnology, Warsaw Genomics.

Bioinformatics

Preprocessing of sequence reads for further analysis was performed using QIIME2 (Bolyen et al., 2019). Following the recommended procedure (Callahan et al., 2016), the sequences were demultiplexed (Illumina 1.8+ Phred+33 encoding) and then were denoised using DADA2 to filter chimeric sequences and combined read pairs and erroneous read combinations (following the suggested workflow (Callahan et al., 2016). The primers were trimmed and reverse sequences were truncated at 249 bp to help reduce the technical quality drop at the end of the reads. The mafft pipeline (Katoh et al., 2002) was applied to generate Amplicon Sequence Variants (ASVs). A total of 9.088.246 reads corresponding to 13.763 unique ASVs over the 68 samples. The average read count per sample was 133.65, with values ranging from 102.966 to 163.287.

Taxonomic assignment with the q2-feature-classifier was performed using a Naive Bayes classifier (Bokulich et al., 2018; Robeson et al., 2020) that was trained on the SILVA reference database (version 138 with 99% OTU from full-length sequences). A phylogenetic tree, along with data on ASV and taxonomy, was generated using the FastTree (Price et al., 2010) and saved as a BIOM file. ASVs that were non-bacterial and were unassigned were removed from the biom file, corresponding to 13.586 unique ASVs over the 68 samples. An average read count per sample was 133.5, ranging between 102.963 – 163.282.

2.4. Statistical analysis

2.4.1 Dietary patterns

The Food Frequency Questionnaire was used to obtain dietary patterns. Dietary patterns were examined using factor analysis with method of principal axis from psych package in R. To enhance interpretability and keep as much dietary data as possible, the analysis was also carried out on participants who completed the Food Frequency Questionnaire but did not complete the entire study. As a result the factor analysis was performed on 544 individuals and 24 food products. Kaiser-Meyer-Olkin (KMO) measurement of sample adequacy and Bartlett test (homogeneity of variance) were used to evaluate whether the obtained correlation matrix was suitable for factor analysis. Since data were not continuous, a heterogenous correlation matrix, consisting of Pearson product-moment correlations were computed using hetcor function from polycor package in R. Oblimin rotation was performed to extract the rotation matrix and factor scores were estimated using Bartlett method.

Red meat and white meat consumption patterns

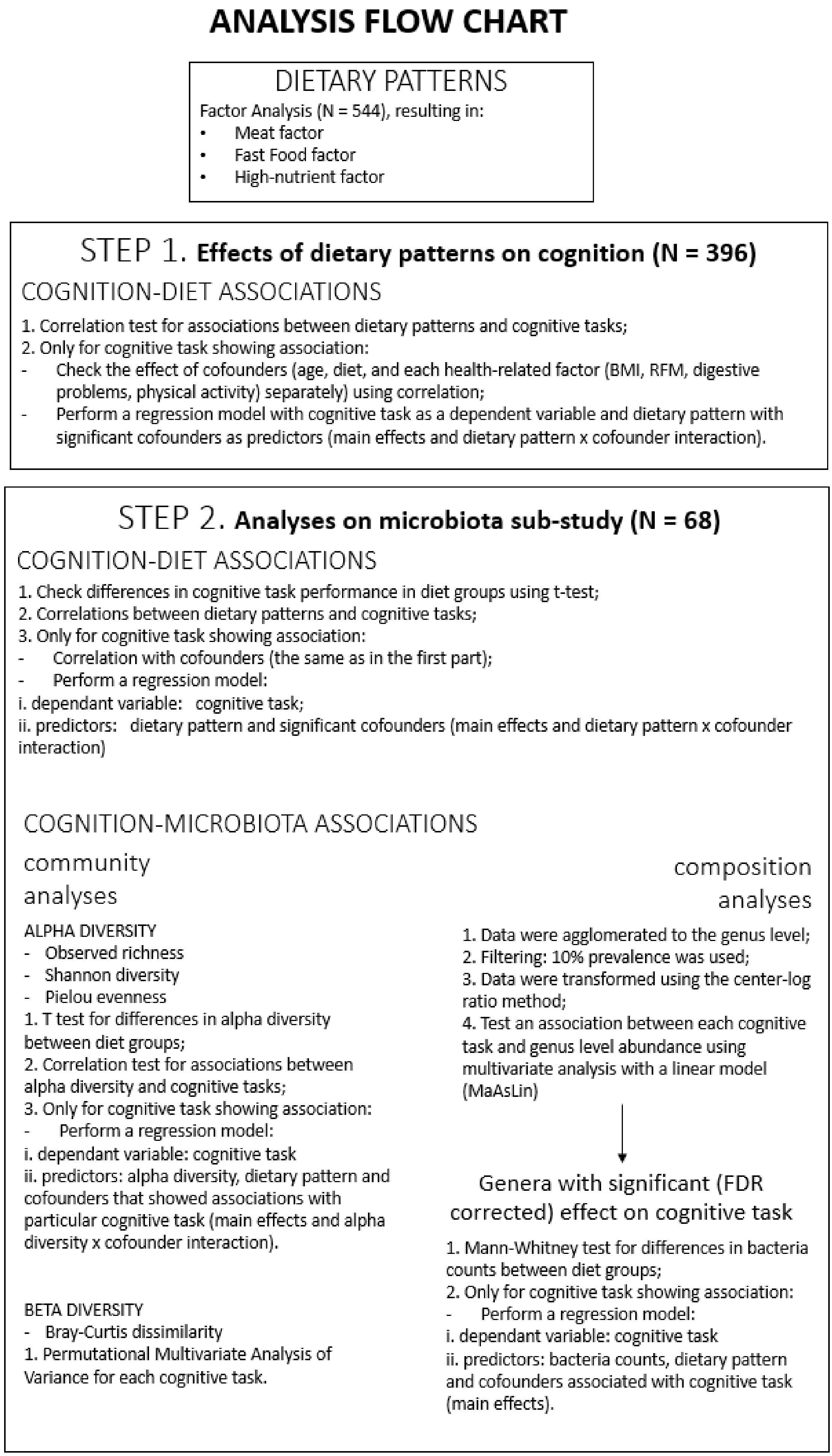
Similar to the previous analysis, I used factor analysis with the principal axis, Oblimin rotation, and the Bartlett method to estimate factor scores to obtain red and white meat consumption. The analysis included 544 participants; however, only meat products (red meat, white meat, lunch meat, canned meat, and fish) were introduced to the algorithm. To obtain factors, I followed the same procedures as before: I measured KMOs, I used the Bartlett test, and I used a heterogeneous correlation matrix (hetcor) due to the non-continuous nature of the variables.

The extraction of dietary patterns was performed differently in the first and second studies. In the first study, PCA (with Varimax rotation) was generated independently for healthy and unhealthy food products based on the FFQ instructions. In the second study, all food products were analyzed using FA (with Oblimin rotation). The Oblimin rotation was used to interpret in context what accounts for the relationship between the factors because foods and even diets are consumed in combinations (Wingrove et al., 2022).

2.4.2. Analysis of the diet and cognition relationship

The analyses were divided in two steps: analysis of the first part of the study (on the whole dataset (n = 396)) and within the microbiota sub-study (n = 68) (Figure 7). The relationships between cognition and dietary patterns were examined for both datasets; the overall dataset included 396 participants, and the microbiota sub-study included 68 females. Because data were taken online and various uncontrollable factors influenced task timing, only accuracy from cognitive tasks was selected for analysis. Scores above 3 standard deviations were removed from analysis. For the entire dataset, Pearson's correlation was used; for the microbiota sub-study, Pearson's correlation was used when both measures were normally distributed, and Spearman's correlation was used when they were not. At first, I looked at how each cognitive task was related to age and health-related factors. Then, each dietary pattern was correlated with cognitive tasks. This was done in order to determine the variables associated with a particular cognitive task. To investigate whether there was an association between age, health-related factors, and dietary patterns on cognitive tasks performance linear regression models as well as generalized linear models (where the data were not normally distributed) were performed. If interaction component was introduced, the continuous variables were centered by subtracting the variable's mean.

Statistical analyses were performed in R (version 4.1.2) in RStudio (version 2021.09.2+382) using packages tidyverse (Wickham et al., 2019), ggstatsplot (Patil, 2021), car (Weisberg & Fox, 2011), psych (Revelle, 2013), polycor (Fox & Adrian, 2022), sjPlot (Lüdecke, 2023), lm.beta (Behrendt, 2023).



ANALYSIS FLOW CHART

DIETARY PATTERNS

Factor Analysis (N = 544), resulting in:

- Meat factor
- Fast Food factor
- High-nutrient factor

STEP 1. **Effects of dietary patterns on cognition (N = 396)**

COGNITION-DIET ASSOCIATIONS

1. Correlation test for associations between dietary patterns and cognitive tasks;
2. Only for cognitive task showing association:
   - Check the effect of cofounders (age, diet, and each health-related factor (BMI, RFM, digestive problems, physical activity) separately) using correlation;
   - Perform a regression model with cognitive task as a dependent variable and dietary pattern with significant cofounders as predictors (main effects and dietary pattern x cofounder interaction).

STEP 2. **Analyses on microbiota sub-study (N = 68)**

COGNITION-DIET ASSOCIATIONS

1. Check differences in cognitive task performance in diet groups using t-test;
2. Correlations between dietary patterns and cognitive tasks;
3. Only for cognitive task showing association:
   - Correlation with cofounders (the same as in the first part);
   - Perform a regression model:

i. dependant variable: cognitive task;

ii. predictors: dietary pattern and significant cofounders (main effects and dietary pattern x cofounder interaction)

COGNITION-MICROBIOTA ASSOCIATIONS

community analyses

ALPHA DIVERSITY

- Observed richness
- Shannon diversity
- Pielou evenness

1. T test for differences in alpha diversity between diet groups;
2. Correlation test for associations between alpha diversity and cognitive tasks;
3. Only for cognitive task showing association:
   - Perform a regression model:

i. dependant variable: cognitive task

ii. predictors: alpha diversity, dietary pattern and cofounders that showed associations with particular cognitive task (main effects and alpha diversity x cofounder interaction).

BETA DIVERSITY

- Bray-Curtis dissimilarity

1. Permutational Multivariate Analysis of Variance for each cognitive task.

composition analyses

1. Data were agglomerated to the genus level;
2. Filtering: 10% prevalence was used;
3. Data were transformed using the center-log ratio method;
4. Test an association between each cognitive task and genus level abundance using multivariate analysis with a linear model (MaAsLin)

Genera with significant (FDR corrected) effect on cognitive task

1. Mann-Whitney test for differences in bacteria counts between diet groups;
2. Only for cognitive task showing association:
   - Perform a regression model:

i. dependant variable: cognitive task

ii. predictors: bacteria counts, dietary pattern and cofounders associated with cognitive task (main effects).

Figure 7. The diet-cognition relationship analysis. Dietary patterns have been identified. Then, their effect on cognitive functioning was evaluated in the N=396 and n=68 groups. The effect of microbiota on cognitive function was also evaluated as part of the microbiota sub-study.

2.4.3. Analysis of the gut microbiota and cognition

Microbiota statistical analyses were performed in R (version 4.1.2) in RStudio (version 2021.09.2+382) using packages phyloseq (McMurdie & Holmes, 2013) (McMurdie & Holmes, 2013) and microbiome (Leo Lahti, Sudarshan Shetty et al., 2017).

Microbiota community

Microbiota alpha and beta diversity analyses were performed without any prevalence filtering on genus or sample level to prevent inducing a bias against less prevalent genera. Alpha diversity metrics provide an summary of the microbial community in terms of its richness (number of taxonomic groups) or evenness (distribution of abundances of the groups) (Willis, 2019). As alpha diversity measures, the observed richness, Shannon diversity index, and evenness Pielou index were calculated. Shapiro-Wilk test was used to assessing normality. Alpha diversity metric is a single diversity value, calculated for each sample, and differences between two (or more) groups can be determined using univariate tests (Kers & Saccenti, 2022). T-test was used to check differences in alpha diversity in diet groups. Correlation test was used to check alpha diversity measures relationships with cognitive performance, and if any alpha diversity index turned out to be significant, the relationships were checked between the particular index and age, health-related factors, and dietary patterns. This was done so that more complex assumptions regarding the relationships between the variables could be used when constructing the model. Based on significant correlations between variables, linear regression models were created along with generalized linear models (if variables were not normally distributed).

Beta diversity measures demonstrate how samples differ from one another by comparing sequence abundances (Kers & Saccenti, 2022). Beta diversity was examined using the Bray-Curtis dissimilarity (Bray & Curtis, 1957). The data were made compositional, where the abundance of each ASV was expressed relative to the total amount and prevalence of ASVs. Bray-Curtis is a distance that explains how different microbial communities have different relative abundances (Kers & Saccenti, 2022). The use of a beta diversity measure meant that all samples were be looked at at the same time. In that case, traditional multivariate tests, such as multivariate ANOVA, have been replaced with permutational multivariate analysis of variance (PERMANOVA) (Anderson, 2001). This is mostly because the number of variables is higher than the number of samples. PERMANOVA was performed using the adonis2 function in the vegan package (Oksanen et al., 2012). Permutation testing was performed for each cognitive task.

Microbiota composition

Compositional analyses were performed at the genus level; the 13.586 ASVs were aggregated into 321 genera. First, genera with a prevalence of greater than 10% across all samples were chosen. Prevalence is a measurement, which describes how often particular microorganisms were found in a given set of samples. After filtering, 206 genera were used in the analysis. The data were then transformed using the center-log ratio method (CLR); the values were no longer counts but the dominance (or lack) for each taxa relative to the geometric mean of all taxa on the logarithmic scale (Aitchison, 1986).

Multivariate analysis with a linear model (MaAsLin2 package in R) (Mallick et al., 2021) was performed to check the potential effects of diet and cognitive tasks, which find associations between microbial abundances. Both a P value and a false discovery rate–adjusted P value (FDR value) were provided.

Mann-Whitney test was used to check differences in significant bacteria counts in diet groups. The Spearman correlation test was then used to see if there were any particular bacteria counts relationships with health-related factors or a particular dietary factor. Generalized linear models were fitted to create models based on significant correlations between variables. The dependent variable was cognitive task performance, and bacteria counts, along with dietary factor or health-related factor (if significant), were predictors in the model. No multicollinearity between predictors were ensured in the analysis. The next step in the analysis was to use a backward selection method to determine the best combination of predictors. The main effects of predictors and interaction terms were then examined.

2.5. Results

2.5.1 Dietary patterns

The Kaiser-Meyer-Olkin (KMO) overall measure of sample adequacy was 0.8, however, food products that separately received a sample adequacy score of less than 0.7 were excluded from further analysis. Finally, dietary patterns were gathered from 22 food products, with the exception of alcohol and energy drinks. The KMO score for the withdrawn dataset was 0.8 and the Bertlett test chi-square: 2980.577, p value < 0.001. Based on the eigenvalues of the factor model, factors with scores > 1 were extracted, resulting in 3 factors. Together, the three factors explained 32% of the total variance. Factor loading matrix organized by food item is included in Figure 8.

Higher consumption of meat and animal fat products was represented by factor 1 (Meat), which contributed to 14% of the original variance, with factor loadings of lunch meat (0.77), white meat (0.74), red meat (0.72). In addition, legume vegetables had a negative average-strong load in this factor (−0.43). Confectionery (0.62), white-flour baked food (0.6), and fast food (0.54) were all associated with factor 2 (Fast Food), which represented 9% of the original variance. Whole grain cereal (0.55), fruits (0.56), vegetables (0.55), and fermented dairy (0.5) formed factor 3, which explained 9% of the total variance.

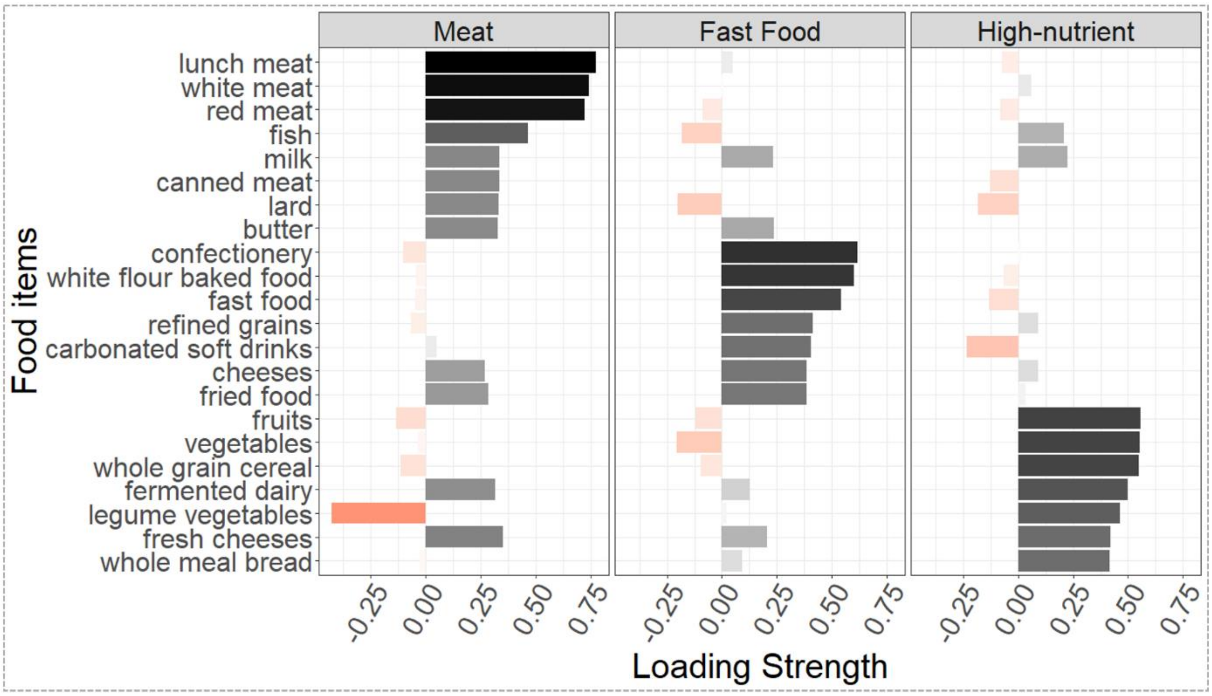


Figure 8. Dietary patterns extracted from factor analysis. Figure show the food items with factor loadings in each dietary factor. Dietary factors were examined using factor analysis with method of principal axis.

The correlations between factors were calculated (Table 9). The Meat factor had a weakly positive correlation ($p < 0.001$) with the Fast Food factor. There was no correlation between the High-nutrient factor and the Fast Food factor.

Table 9. Pearson correlations among factors describing dietary factors from the FFQ questionnaire

	Meat	**Fast Food**
Meat	–	
Fast Food	r: 0.15***	–
High-nutrient	r: –0.3	r: –0.03

*** *p* value < 0.001.

Red and White meat patterns were gathered from 5 meat products – red meat, white meat, lunch meat, canned meat and fish. KMO overall measure of sample adequacy was 0.75 and the Bertlett test chi-square: 751.963, p value < 0.001 and two factors were extracted. Together, the two factors explained 49% of the total variance. A factor loading matrix organized by food item is included in Figure 9.

The first factor (Red meat) represented higher consumption of lunch meat (0.74), red meat (0.67) and canned meat (0.56) and explained 26% of the total variance. White meat (0.85) and fish (0.55) consumption were associated with the second factor (White meat), which explained 22% variance. The correlation between Red meat and White meat factors was statistically significant (r = 0.58, p < 0.001).

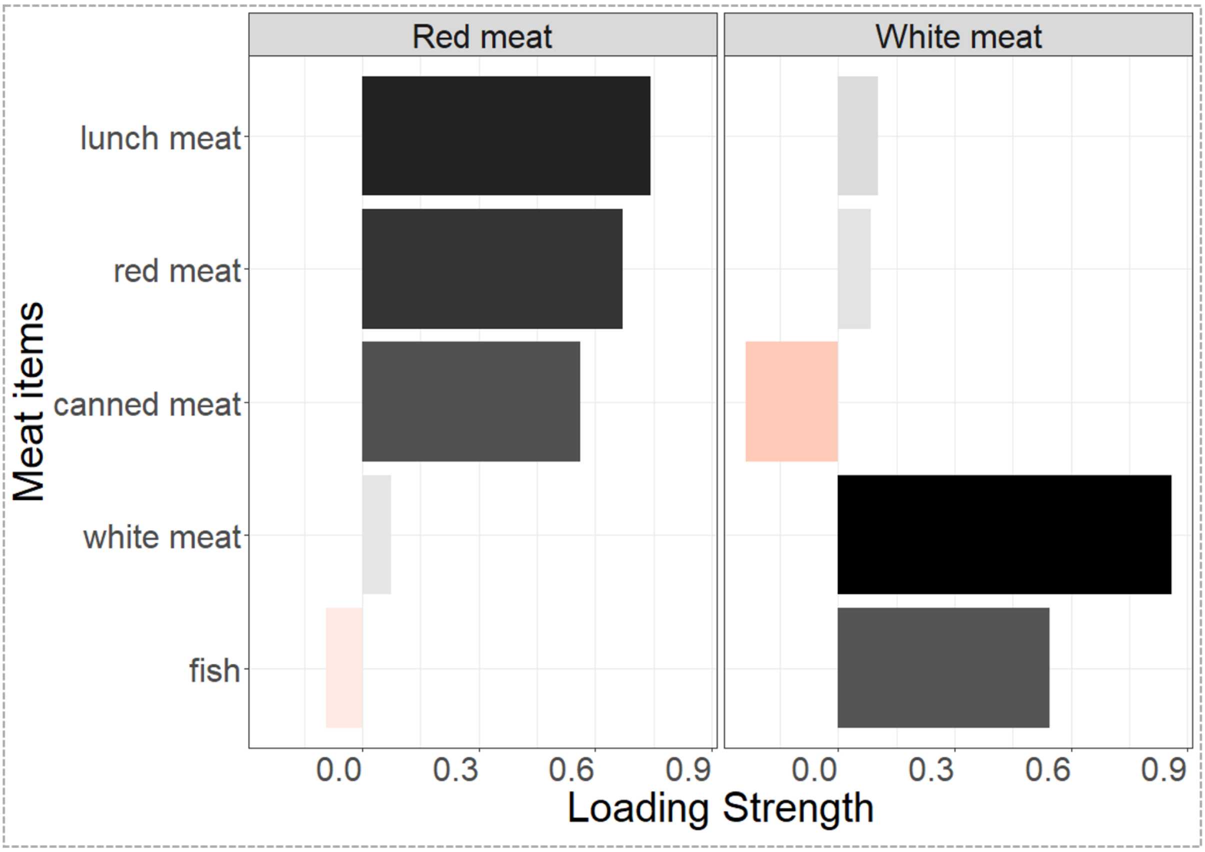


Figure 9. Red meat and white meat consumption obtained from factor analysis with a principal axis method. Figure show various meat items loading differentialy Red and White meat factor.

2.5.2. Step 1. Effects of dietary factors on cognition

2.5.2.1 Participants characteristics

The first part of the study included 396 participants between the age 18 and 70 (339 females and 57 males). The characteristics of the participants are summarized in Table 10. A variety of health and lifestyle factors were considered. The study population is predominately female; the majority of participants (59.3%) were employed, resided in a large city (73.2%), and had a moderate financial situation.

In terms of health, 40.9% of participants had digestive issues, and 59.5 had sedentary lifestyle. On average, participants scored 26 (SD = 8.08) on fatigue score, 22.32 (SD = 3.78) on Body Mass Index (BMI) and 30.95 (SD = 6.54) on Relative Fat Mass (RFM) index. On weekdays, the majority (74.2%) and on weekends (56.3%) slept 7 to 8 hours per day, with a tendency to sleep 9 hours or more (39.1%). In total, 31.1% of participants admitted to drinking alcohol, while 35.1% smoked or smoked cigars. Omnivores were the most common (52.2%), followed by vegetarians (31.5%) and people on elimination diets (16.1%). The mean score for dietary knowledge was M=10.47, with a standard deviation of SD=2.94. The majority of the WHO Quality of Life questionnaire characteristics were similar across the entire dataset.

Table 10. Descriptive statistics of participants characteristics.

Characteristics	**I. All** **(*n* = 396)** Number/Mean (SD)
Sex	♀ 339; ♂ 57 ♀ 85.6%; ♂ 14.3%
Age	29.75 (9.03)
Employment	59.3%
Domicile	
country	10.8%
small town	4.7%
medium town	11.1%
big town	73.2%
Financial issues	
high income	25.2%
moderate income	65.1%
low income	9.5%
WHO Quality of Life	
physical health	13.96 (2.9)
psychological	13.65 (3.03)
social relationships	13.35 (3.35)
environment	14.51 (2.29)
Fatigue score	26.00 (8.08)
Body Mass Index	22.32 (3.78)
Relative Fat Mass	30.95 (6.54)
Digestive problems	40.9%
Physical activity	

Characteristics	**I. All** **(*n* = 396)** Number/Mean (SD)
sedentary	59.5%
light	40.4%
Sleep quality (week)	
six hours or less	14.3%
seven or eight hours	74.2%
nine hours and more	11.3%
Sleep quality (weekend)	
six hours or less	4.5%
seven or eight hours	56.3%
nine hours and more	39.1%
Smoking	35.1%
Alcohol	31.1%
Dietary knowledge	10.47 (2.94)
Diet type	
omnivore	52.2%
vegetarian	31.5%
elimination	16.1%

SD = standard deviation

2.5.2.2 Cognitive tasks performance as a function of age and health

Associations between each cognitive task's accuracy and age and health-related variables were analyzed (Table 11). To account for the skewed character of distribution of the Multitasking task score, I decided to use the Spearman correlation and Mann-Whitney tests. In addition to the disparity between diet type categories, the Kruskal-Wallis test was applied to examine the relationship between diet and both cognitive tasks.

Age had a significant negative correlation with both Multitasking task and MRT task; the higher the age, the lower the cognitive tasks performance ($p < 0.001$). The RFM index had a significant negative effect on the Mental Rotation Task ($p < 0.001$); task performance decreased as the RFM index increased. Although there was a tendency effect, the BMI index had a negative impact on Multitasking performance (p = 0.08).

Table 11. Associations of Multitasking and Mental rotation task (MRT) age and health-related factors.

	Multitasking		**MRT**	
Age	rho: –0.33***	-	r: –0.19***	-
Fatigue	rho: –0.005	-	r: –0.04	-
Body Mass Index	rho: –0.09°	-	r: –0.03	-
Relative Fat Mass	rho: –0.2	-	r: –0.16***	-
Digestive problems	Z: –0.981	Mean (SD) *yes* M=1272.6(689.9) *no* M=1352.1(601.9)	t: –0.6068	Mean (SD) *yes* M=11.25 (5.3) *no* M=10.91 (5.4)
Diet type	H: 0.544	Mean (SD) *omnivore* M=1275.3(706.9) *vegetarian* M=1381.5(465.9) *elimination* M=1342.9(695.5)	H: 0.574	Mean (SD) *omnivore* M=10.86(5.3) *vegetarian* M=11.24(5.2) *elimination* M=11.3(5.8)
Physical Activity	Z: –0.32	Mean (SD) *light* M=1353.4(526.8) *sedentary* M=1295.9(706.8)	t: –0.2498	Mean (SD) *light* M=10.97 (5.3) *sedentary* M=11.11 (5.4)

r = r Pearson value; rho = rho Spearman value; t = Student t-test; Z = Mann-Whitney test; H = Kruskal-Wallis test. Asterisks indicate statistical significance: ° *p* value < 0.09, *** *p* value < 0.001.

2.5.2.3. Cognitive tasks performance correlations with dietary factors

The calculated correlations between cognitive tasks and dietary factors are presented in Table 12. I decided to use Spearman correlation for Multitasking task, as well as Meat and Red meat dietary factors because of a not normal distribution of the variables (many participants eliminated red meat from theirs diet.). There was no significant correlations between cognitive performance and dietary factors.

Table 12. Correlations of Multitasking task and MRT task with dietary factors.

	Cognitive tasks	
	Multitasking	**MRT**
Meat	rho: -0.02	rho: -0.03
Fast Food	rho: 0.09	r: -0.02
High-nutrient	rho: -0.04	r: 0.01
Red meat	rho: -0.05	rho: -0.07
White meat	rho: 0.01	r: -0.08

r = r Pearson value; rho = rho Spearman value;

Age and Relative Fat Mass correlations with dietary factors

Given the lack of a significant correlation between cognitive tasks and dietary variables, correlations between age and the RFM index were examined with each dietary factor.

Age and RFM index showed a significant correlation with the Mental Rotation Task (Table 11). Age had a significant positive correlation ($p < 0.05$) with the Meat factor and a significant negative correlation ($p < 0.01$) with the Fast Food factor (Table 13). The higher the Age, the higher the Meat factor and the lower the Fast Food factor. The RFM index had a significant positive correlation ($p < 0.05$) only with the Meat factor. The higher RFM index, the higher Meat factor. Neither Age nor RFM had a significant correlation with the High-nutrient factor.

Table 13. Correlations of Multitasking task and MRT task with dietary factors.

	Age	**RFM**
Meat	rho: 0.13*	rho: 0.11*
Fast Food	r: –0.16**	r: -0.01
High-nutrient	r: 0.05	r: 0.01

r = r Pearson value; rho = rho Spearman value; * p value < 0.05

Mental Rotation Task performance predicted by age, RFM index and Meat

Linear regressions were used to predict Mental Rotation task performance based on age, RFM index, and Meat dietary factor as suggested by preliminary correlations. The first model included main effects of age, RFM index and Meat, and the interaction effects (Age x Meat and RFM x Meat). The age and RFM index predictors were centered prior to the analysis.

The further analysis included the examination of single interactions that were determined to be statistically significant (Table 14). Not-significant interaction effects were eliminated from the model. The final model for the Mental Rotation task included age ($\beta = -0.165$), RFM index ($\beta = -0.113$), Meat factor ($\beta = -0.017$, not significant), and the interaction between RFM index and Meat factor ($\beta = -0.111$) as predictors. The final model was statistically significant ($F(4, 374) = 6.661$, $p < 0.001$) with an R2 of 0.07 (Table 14), indicating the possibility of a significant interaction between RFM index and Meat factor on cognitive task performance.

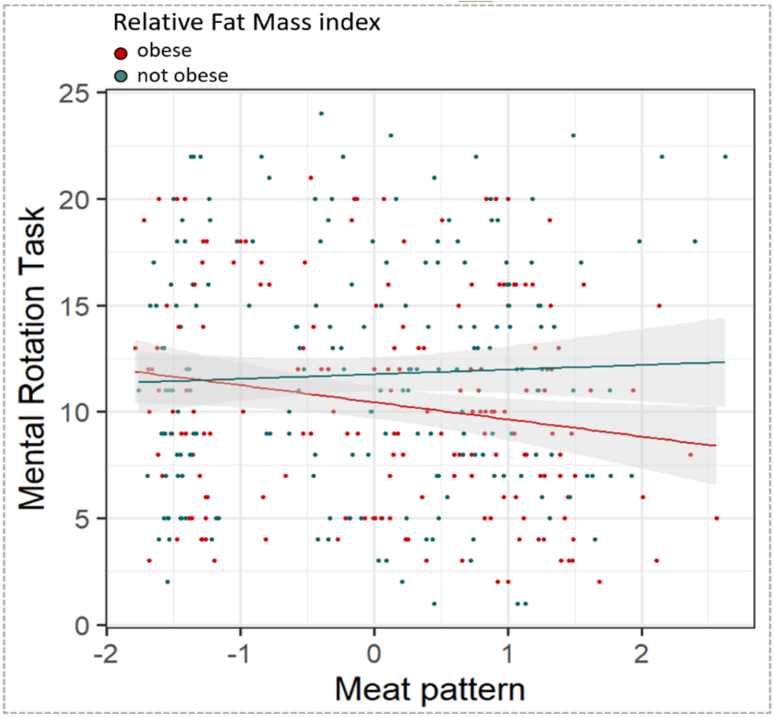


Figure 10. Linear regression analyses of the associations between obese and not obese Relative Fat Mass groups and Mental Rotation Task predicted by Meat dietary factor.

When examining the interaction plot we can see that the Mental Rotation task performance decreases as the RFM index and Meat consumption increases, whereas a higher Meat consumption with lower RFM index scores had no significant effect on cognitive task performance (Figure 10). Obese group was related with higher RFM index scores.

Table 14. Summary of linear regression analysis for interaction between Meat factor, age, and RFM index predicting Mental Rotation Task performance for all participants (n = 396).

Interaction Model							
Variables	**B**	**SE**	**β**	**t**	***p***	**R^2**	**F Statistic**
Model					0.000	0.07	5.336
Age	-0.097	0.03	-0.167	-3.218	0.001		
RFM	-0.09	0.041	-0.113	-2.203	0.02		
Meat	-0.09	0.243	-0.018	-0.372	0.709		
Age x Meat	0.008	0.026	0.017	0.319	0.749		
RFM x Meat	-0.082	0.037	-0.115	-2.229	0.02		
Final Model							
Variables	**B**	**SE**	**β**	**t**	***p***	**R^2**	**F Statistic**
Model					0.000	0.07	6.661
Age	- 0.096	0.029	-0.165	-3.212	0.001		
RFM	-0.091	0.041	-0.113	-2.206	0.02		
Meat	-0.085	0.242	-0.017	-0.354	0.723		
RFM x Meat	-0.079	0.036	-0.111	-2.212	0.03		

B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient. The dependent variable was the Mental Rotation task score.

To explain the interaction effect between the RFM index and the Meat factor, I divided participants into obese (n = 172) and not-obese (n = 195) groups based on the RFM index. Next, regression analysis was conducted separately for each subgroup, using age and Meat factor as predictors.

The model for the obese group (F(2, 166) = 6.064, p = 0.003) showed the effect of age, but no significant association with the Meat factor. Performance on the Mental Rotation task decreased with age (β = −0.207) (Table 15). The model for the not-obese group that was not significant.

Table 15. Explanations of the interaction effects (RFM x Meat) grouped by RFM index (obese and not-obese participants).

Variables	**B**	**SE**	**β**	**t**	***p***	**R^2**	**F Statistic**
Not obese					0.131	0.02	2.068
Age	-0.097	0.048	-0.143	-1.987	0.048		
Meat	0.236	0.365	0.046	0.647	0.518		
Obese					0.003	0.07	6.064
Age	-0.105	0.038	-0.207	-2.714	0.007		
Meat	-0.549	0.345	-0.121	-1.588	0.114		

B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient. The dependent variable was the Mental Rotation task score.

Red meat and White meat associations with age and RFM index

Furthermore, more detailed analyses of meat type consumption have been conducted. Because the Mental Rotation Task was associated with the variables age and RFM index, correlations between the White meat and Red meat factors were investigated (Table 16).

Red meat factor had positively tendency ($p < 0.06$) with both age and RFM index variables. White meat factor had a positive correlation with RFM index ($p < 0.05$).

Table 16. Correlations of Multitasking task and MRT task with dietary factors.

	Age	**RFM index**
Red meat	rho: 0.1°	rho: 0.1°
White meat	r: 0.04	r: 0.12*

r = r Pearson value; °*p* value < 0.06, **p* value < 0.05

Mental Rotation Task performance predicted by age, RFM index and White or Red meat factor

Separate linear models for Red meat and White meat factors were conducted, despite that Red meat had only a tendency. As suggested by preliminary correlations, the first model predicted the Mental Rotation task performance with age, the RFM index and Red meat factor as predictors, while the second model used RFM index and White meat factor as a predictors. The age and RFM index predictors were centered prior to the analysis.

The first model included the main effects of age, RFM index, and Red meat consumption, as well as their respective interaction effects (Age x Red meat and RFM x Red meat). The model ($F(5, 372) = 4.952$, $p < 0.001$) showed the effect of age ($\beta = -0.171$) and effect of RFM index ($\beta = -0.106$), but there was no significant association between Red meat consumption and its interaction with age and RFM index. Performance on the Mental Rotation task declined with increasing age and RFM index (Table 17).

The second model included the main effects of RFM index, White meat and the interaction effect (RFM x White meat). The model (F(3, 380) = 4.47, $p < 0.05$) showed the main effect of RFM index (β = −0.151), but there was no association between White meat consumption. The interaction term was not significant. Performance on the Mental Rotation task declined when RFM index increased (Table 17).

Table 17. Summary of linear regression analysis for interaction between age and RFM index with each type of meat consumption (red or white) predicting Mental Rotation Task performance for all participants (n = 396).

Red meat Model

Variables	**B**	**SE**	**β**	**t**	***p***	**R^2**	**F Statistic**
Model					0.000	0.06	4.952
Age	-0.099	0.03	-0.171	-3.252	0.001		
RFM	-0.085	0.041	-0.106	-2.062	0.04		
Red meat	-0.217	0.237	-0.047	-0.917	0.36		
Age x Red meat	0.004	0.023	0.01	0.189	0.85		
RFM x Red meat	-0.048	0.035	-0.072	-1.369	0.17		

White meat Model

Variables	**B**	**SE**	**β**	**t**	***p***	**R^2**	**F Statistic**
Model					0.03	0.03	4.47

RFM	-0.122	0.041	-0.151	-2.965	0.00
White meat	-0.144	0.242	-0.03	-0.595	0.55
RFM x White meat	-0.061	0.037	-0.082	-1.628	0.1

B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient. The dependent variable was the Mental Rotation task score.

Multitasking task performance predicted by age and Meat

Given that the Multitasking task score variable did not have a normal distribution and was highly left-skewed, a generalized linear model with a quasi-based family distribution was used to predict cognitive task performance based on age and Meat dietary factor. The age predictor were centered prior to the analysis.

The interaction model included the main effects of age, Meat factor, and their interaction (Age x Meat). The model was statistically significant (F(3, 377) = 19.85, p < 0.001) with an R2 of 0.14 (Table 18). The model showed an effect of age (β = -0.355), but neither Meat factor nor interaction had a significant effect on cognitive task performance.

Table 18. Summary of generalized linear model for interaction between Meat factor and age predicting Multitasking task performance for all participants (n = 396).

Interaction Model							
Variables	**B**	**SE**	**β**	**t**	***p***	**R^2**	**F Statistic**
Model					0.000	0.14	19.85
Age	-25.275	3.475	-0.355	-7.273	0.000		
Meat	-5.715	27.618	-0.01	-0.207	0.836		

Age x Meat	-3.165	2.947	-0.052	-1.074	0.283

B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient. The dependent variable was the Multitasking task score.

2.5.3. Step 2. Analyses on microbiota sub-study

2.5.3.1. Participants characteristics

The microbiota sub-study included 68 females aged 20 to 54, with 31 following a vegetarian diet and 37 following an omnivore diet. The characteristics of the participants are summarized in Table 19. The same health and lifestyle factors were taken into consideration as in the previous part.The majority of participants (61.7%) were employed, resided in a large city (82.3%), and had a moderate financial situation.

In terms of health, 38.2% of participants had mild digestive issues, particularly among the omnivore diet group (48.6%), and 50.2% led a sedentary lifestyle. On weekdays (75%) and weekends (50%), the majority (75%) slept 7 to 8 hours per day, interchangeable with 9 hours or more (48.5%). In total, 36.7% admitted to drinking alcohol, while 27.8% smoked or smoked cigars. However, the vegetarian group had a higher proportion of people who smoked. Dietary knowledge had a mean score of M=10.82 with a standard deviation of SD=2.99 that was unaffected by diet group. The majority of the WHO Quality of Life questionnaire characteristics, Body Mass Index and Relative Fat Mass index, were consistent across the entire dataset.

Table 19. Descriptive statistics of participants characteristics at: I. all participants, II. each diet group.

Characteristics	**I. All** (*n* = 68) Number/Mean (SD)	**II. Omnivore diet group** (*n* = 37) Number/Mean (SD)	**II. Vegetarian diet group** (*n* = 31) Number/Mean (SD)
Age	29.83 (8.44)	29.8 (8.69)	29.8 (8.28)
Employment	61.7%	64.8%	58.1%
Domicile			
country	8.8%	8.1%	9.7%
medium town	8.8%	13.5%	3.2%
big town	82.3%	78.3%	87.1%
Financial issues			
high income	30.8%	29.7%	32.3%
moderate income	61.7%	62.1%	61.2%
low income	7.3%	8.1%	6.6%
WHO Quality of Life			
physical health	13.33 (22.7)	13.3 (2.72)	13.4 (2.64)
psychological	13.31 (2.4)	13.2 (2.58)	13.9 (2.07)
social relationships	12.7 (3.3)	12.5 (3.48)	13 (3.08)
environment	13.7 (1.6)	13.8 (1.56)	13.6 (1.67)
Fatigue score	23.48 (7.32)	24 (7.01)	22.9 (7.75)
Body Mass Index	21.24 (2.6)	21.8 (2.67)	20.6 (2.39)
Relative Fat Mass	32.18 (5.33)	32.6 (5.61)	31.7 (5.04)
Digestive problems	38.2%	48.6%	25.8%
Physical activity			
sedentary	60.2%	70.2%	48.3%
light	39.7%	29.7%	51.6%
Sleep quality (week)			
six hours or less	8.8%	5.4%	12.9%
seven or eight hours	75%	78.3%	70.9%
nine hours and more	16.1%	16.2%	16.1%
Sleep quality (weekend)			
six hours or less	1.4%	-	3.2%
seven or eight hours	50%	40.5%	61.3%
nine hours and more	48.5%	59.4%	35.4%
Smoking	27.9%	16.2%	41.9%
Alcohol	36.7%	35.1%	38.7%
Dietary knowledge	10.82 (2.99)	10.8 (2.91)	10.8 (3.13)

SD = standard deviation. Asterisks indicate statistical significance: ° *p* value < 0.09, * *p* value < 0.05, *** *p* value < 0.001.

2.5.3.2. Associations of cognitive tasks with age and health-related factors

The accuracy of each cognitive task was correlated with age and health-related variables (Table 20). To account for the skewed character of distribution of the Sternberg task score, I decided to use the Spearman correlation and Mann-Whitney tests.

The BMI index had a significant negative effect on the Digit Span task ($p < 0.05$); as weight increased, performance on the task decreased. Fatigue score had a negative relationship with CVLT score ($p < 0.05$) - the higher the fatigue, the lower the test performance. There were tendency effects of the RFM index, which had a negative impact on CVLT task performance ($p = 0.06$), and of age, which had a positive impact on episodic task performance ($p = 0.06$).

Table 20. Associations of sub-study cognitive tasks with age and health-related factors.

	Episodic **statistic Mean(SD)**	**Sternberg** **statistic Mean(SD)**	**Digit Span** **statistic Mean(SD)**	**CVLT** **statistic Mean(SD)**
Age	r: 0.23°	rho: -0.1	r: -0.1	r: -0.03
Fatigue	r: -0.13	rho: -0.17	r: -0.08	r: -0.27*
Body Mass Index	r: 0.05	rho: -0.13	r: -0.26*	r: -0.17
Relative Fat Mass	r: 0.19	rho: 0.02	r: -0.01	r: -0.24°
Digestive problems	t: -0.748 *yes* M=38.8(5.9) *no* M=39.8(5.1)	U: 524 *yes* M=139.9(10.6) *no* M=142.3(5.2)	t: 0.509 *yes* M=13.1(3.3) *no* M=12.7(2.2)	t: -1.177 *yes* M=61.4(8.7) *no* M=63.9(7.8)
Diet type	t: -1.057 *omnivore* M=38.8(5.6) *vegetarian* M=40.2(5.1)	U: 503 *omnivore* M=141.7(7.7) *vegetarian* M=141.1(7.7)	t: 1.357 *omnivore* M=13.3(3.1) *vegetarian* M=12.3(3.3)	t: 0.21 *omnivore* M=63.1(8.1) *vegetarian* M=62.7(8.4)
Physical Activity	t: -0.857 *light* M=38.7(4.7) *sedentary* M=39.9(5.7)	U: 480.5 *light* M=143.0(5.2) *sedentary* M=140.4(8.9)	t: -1.178 *light* M=12.3(3.8) *sedentary* M=13.2(2.8)	t: 1.496 *light* M=64.9(7.3) *sedentary* M=61.8(8.5)

r = r Pearson value; rho = rho Spearman value; t = Student t-test, U = Mann-Whitney test. Asterisks indicate statistical significance: ° p value <= 0.06, * p value < 0.05; ** p value < 0.01, *** p value < 0.001.

2.5.3.3. Cognitive tasks associations with dietary factors

Correlations were calculated to see if there were any associations between cognitive tasks and dietary factors (Table 21). Fast Food had a significant negative impact on Episodic task performance ($p < 0.05$). The task was performed better with a lower-intensity dietary factor. There were no other significant effects.

Table 21. Correlations between cognitive tasks and dietary factors.

	Meat	**Fast Food**	**High-nutrient**
Episodic	r: -0.04	r: -0.29*	r: 0.04
Sternberg	rho: -0.06	rho: 0.02	rho: 0.15
Digit Span	r: 0.08	r: 0.16	r: -0.1
CVLT	r: 0.1	r: -0.09	r: -0.01

r = r Pearson value; rho = rho Spearman value; * *p* value < 0.05.

Episodic task score predicted by Fast Food and age

Linear regression was used to predict Episodic Memory task performance based on Fast Food dietary factor and age (because age showed a statistical tendency in the correlation with this task). The regression model included the main effects of age and Fast Food factor and the interaction effect (Age x Fast Food). The age predictor was centered prior to the analysis, and Fast Food factor were a factor in the factor analysis.

The interaction model was statistically significant ($F(3, 64) = 3.831$, $p < 0.01$) with an R2 of 0.15 (Table 22), but neither the main effects terms nor the interaction terms were significant.

Table 22. Summary of linear regression analysis for interaction between Fast Food factor and age predicting Episodic task performance for microbiota sub-study (n = 68).

Interaction Model							
Variables	**B**	**SE**	**β**	**t**	***p***	**R^2**	**F Statistic**
Model					0.01	0.15	3.831
Age	0.146	0.076	0.228	1.912	0.06		
Fast Food	-0.948	0.477	-0.233	-1.988	0.05		
Age x Fast Food	0.108	0.064	0.197	1.673	0.1		

B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient. The dependent variable was the Episodic task score.

2.5.3.4. Cognitive tasks associations with microbiota

Cognitive tasks associations with alpha diversity

The correlation between cognitive tasks and microbiota diversity is shown in Table 23. Both the observed richness measure and the Shannon diversity index had a positive effect on Episodic task performance; the higher the score on the community measure, the better the task performance ($p < 0.05$ for both). The Pielou evenness index was associated with the Digit Span task ($p < 0.01$). The more evenly distributed the microbiota, the better the performance on cognitive task. There were no other significant correlations.

Table 23. Correlations of cognitive tasks with microbiota diversity measures

	Observed richness	**Shannon diversity**	**Pielou evenness**
Episodic	r: 0.24*	r: 0.25*	r: 0.19

	Observed richness	Shannon diversity	Pielou evenness
Sternberg	rho: 0.003	rho: 0.06	rho: 0.06
Digit Span	r: -0.1	r: 0.09	r: 0.33**
CVLT	r: 0.12	r: -0.006	r: -0.04

r = r Pearson value; rho = rho Spearman value. Asterisks indicate statistical significance: * *p* value < 0.05, ** *p* value < 0.01.

Correlations between different alpha diversity measures were then calculated (Table 24). The Shannon diversity index was chosen for further analysis because it was significantly associated with the other diversity measures (p < 0.001) and related to Episodic memory task.

Table 24. Pearson correlations among microbiota alpha diversity measures

	Observed richness	Shannon diversity
Observed richness	–	
Shannon diversity	r: 0.79***	–
Pielou evenness	r: 0.23°	r: 0.75***

Asterisks indicate statistical significance: ° *p* value < 0.08; *** *p* value < 0.001.

Furthermore, associations between Shannon diversity and diet, age, and Fast Food factor were investigated. Age and Fast Food were found to be related to the Episodic task and the diet was the variable based on which respondents were recruited. I performed the Pearson correlation for linear variables and Student t test for diet variable. None of the performed analyses were significant (Table 25).

Table 25. Shannon diversity associations with Diet, Fast Food and Age

	Diet		Fast Food	Age
		Mean (SD)		
Shannon diversity	t: 0.39	*omnivore* 4.45 (0.24)	r: -0.18	r: 0.03
		vegetarian 4.42 (0.36)		

r = r Pearson value; t = Student t-test.

Episodic task score predicted by Shannon diversity index, Fast Food factor and Age

Linear regression was used to predict Episodic task performance and the model included age, Fast Food factor and Shannon diversity as predictors. Preliminary correlations were used as a guide for how the model was implemented. The regression model was statistically significant (F(3, 63) = 3.748, p < 0.05) with an R2 of 0.15 (Table 26), however, none of the predictors were statistically significant. Despite this, I eliminated the age predictor because it was the only one that did not indicate any trend. The final model was statistically significant (F(2, 64) = 4.385, p < 0.05, R2=0.12) and showed the effect of Fast Food factor (β = −0.248) however the Shannon diversity index continued to had no significant effect.

Table 26. Summary of linear regression analysis for Shannon diversity, Fast Food factor and age predicting Episodic task performance for microbiota sub-study (n = 68).

Regression Model							
Variables	**B**	**SE**	**β**	**t**	***p***	**R^2**	**F Statistic**
Model					0.02	0.15	3.748

Age	0.113	0.074	0.178	1.515	0.13		
Fast Food	-0.867	0.479	-0.216	-1.811	0.07		
Shannon diversity	3.617	2.106	0.202	1.718	0.09		

Final Model

Variables	**B**	**SE**	**β**	**t**	***p***	**R^2**	**F Statistic**
Model					0.02	0.12	4.385
Fast Food	-0.996	0.476	-0.248	-2.09	0.04		
Shannon diversity	3.617	2.127	0.202	1.7	0.09		

B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient. The dependent variable was the Episodic task score.

Cognitive tasks associations with microbiota beta diversity

I used permutational multivariate analysis of variance (PERMANOVA) to measure of similarity or dissimilarity among microbiota communities, taking each cognitive task's performance into account. None of the cognitive tasks did not significantly affect gut microbial community (Bray-Curtis beta diversity).

Cognitive tasks associations with microbial taxa

I performed multivariate associations analysis with linear models (MaAsLin2) to determine association between various bacteria counts and each cognitive task. Results found a tendency effect of *Senegalimassilia* taxa on the Episodic Memory task scores. Higher scores in cognitive task were associated with lower abundance of *Senegalimassilia* (effect size =

−0.2082; q value = 0.05) (Table 27, Figure 11A). The analysis showed no significant models with other cognitive tasks. Only adjust p value (q value) was taken into account, because multiple comparisons were performed.

Additionally, I performed a Spearman correlation between *Senegalimassilia* counts and Episodic memory task. The correlation was significant (rho = −0.31, $p < 0.01$) (Figure 11B).

Table 27. Summary multivariate associations analysis with linear models for *Senegalimassilia* taxa.

Multivariate assosiations analysis with linear model						
	effect size	**SE**	**N**	**N not 0**	**p value**	**q value**
Senegalimassilia	-0.2082	0.0542	68	22	0.0002	0.05

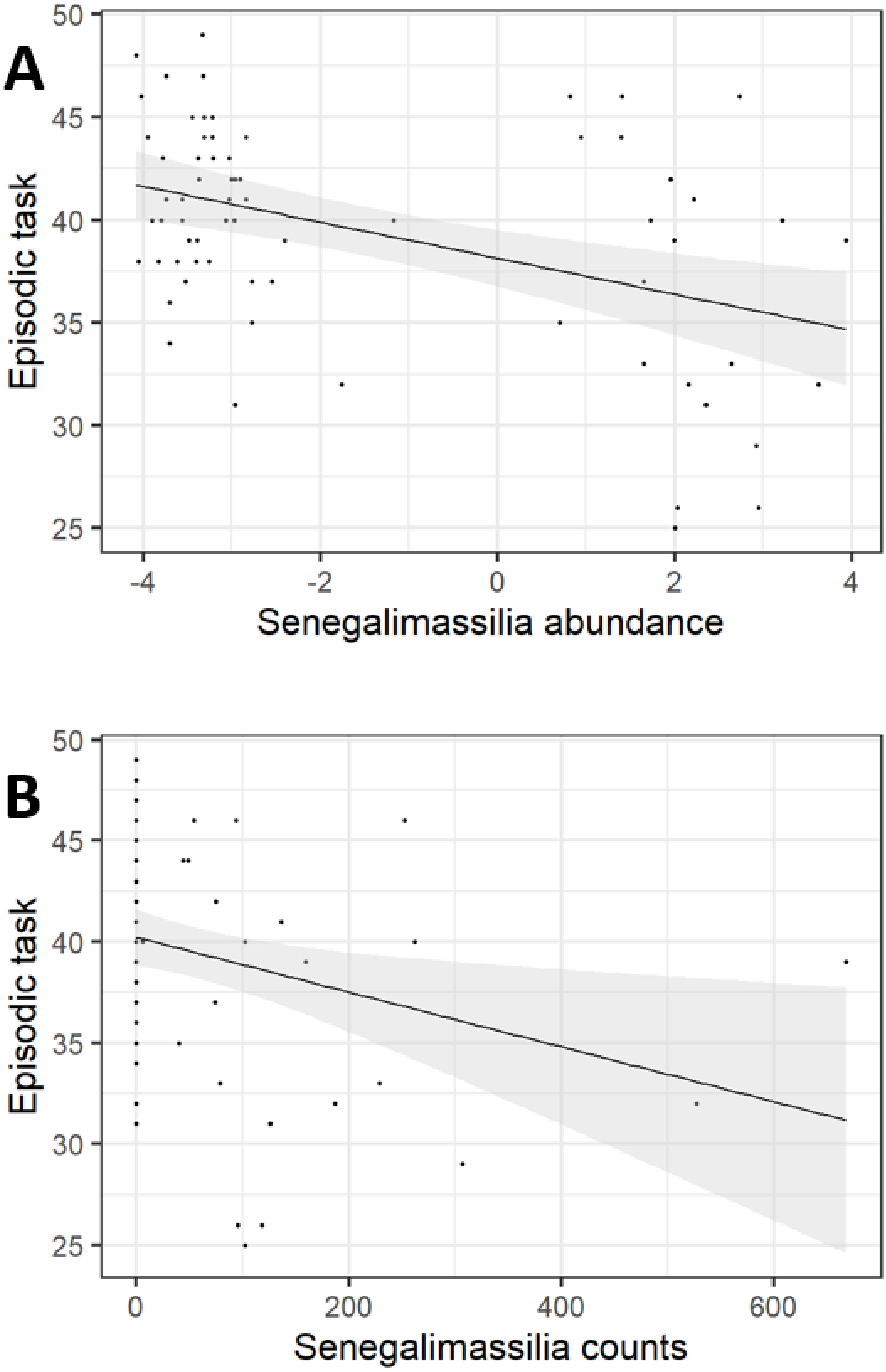


Figure 11. Episodic task performance associated with Senegalimassilia. A. Bacteria abundance is a dominance (or lack) for each microorganism relative to the others. B. Bacteria counts are a measurement or estimate of the number of bacteria present in a sample.

Associations of Senegalimassilia with age and health-related factors and with dietary factors

Furthermore, associations between *Senegalimassilia* counts and diet, age, and Fast Food factor were investigated. Age and Fast Food were found to be related to the Episodic task and the diet was the variable based on which respondents were recruited. I performed the Spearman correlation for linear variables and Mann-Whitney U test for diet variable. Except for a correlation trend toward an age ($p = 0.08$), no results were statistically significant (Table 28).

Table 28. Associations of *Senegalimassilia* with Diet, Fast Food and age

	Diet		**Fast Food**	**Age**
Senegalimassilia	U: 478	Mean (SD) *omnivore* 67.08 (126.8) *vegetarian* 42.03 (111.8)	rho: 0.08	rho: -0.21°

rho = rho Spearman value; U = Mann-Whitney test; °*p* value < 0.09.

Episodic task score predicted by Senegalimassilia and Fast Food factor

Despite the fact that MaAsLin2 analysis revealed that *Senegalimassilia* had only a trend effect, I decided to fit a generalized linear model with a quasi-based family distribution. The first model included the main effects of age, Fast Food factor and *Senegalimassilia*.

The further analysis included the examination of single effects that were determined to be statistically significant (Table 29). Non significant predictors were eliminated from the model. The final model of performance prediction for the Episodic task included Fast Food factor ($\beta = -0.289$) and *Senegalimassilia* ($\beta = -0.305$). The final model was statistically significant ($F(2, 65) = 6.878$, $p < 0.01$) with an R2 of 0.17 (Table 29).

Furthermore, the association between *Senegalimassilia* and Episodic memory in a group of 22 persons with the presented bacteria gene was examined using Spearman correlation. The result was not significant (rho: -0.31, p > 0.05)

Table 29. Summary of linear regression analysis for *Senegalimassilia* counts, Fast Food factor and age predicting Episodic task performance for microbiota sub-study (n = 68).

First Model							
Variables	**B**	**SE**	**β**	**t**	***p***	**R²**	**F Statistic**
Model					0.003	0.19	5.02
Age	0.083	0.074	0.130	1.119	0.26		
Fast Food	-1.079	0.464	-0.265	-2.322	0.02		
Senegalimassilia	-0.012	0.005	-0.279	-2.44	0.01		
Final Model							
Variables	**B**	**SE**	**β**	**t**	***p***	**R²**	**F Statistic**
Model					0.002	0.17	6.878
Fast Food	-1.176	0.457	-0.289	-2.571	0.01		
Senegalimassilia	-0.013	0.005	-0.305	-2.708	0.008		

B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient. The dependent variable was the Episodic task score.

2.6 Summary

The purpose of the study was to examine the association between dietary habits, gut microbiota, and cognitive performance in an adult population. According to the effects of dietary patterns on cognition, the frequency of meat consumption (Meat factor) influence the effects of metabolic adiposity (as measured by the RFM index) on cognitive performance. Performance on the Mental Rotation task declined as the Meat factor score increased, but only in the group with higher RFM index scores. For participants who had average RFM scores, Meat consumption had no significant effect. RFM is one of a number of anthropometric indices created to correlate with body fat distribution and total fat mass more precisely (Cichosz et al., 2022). It is associated with metabolic adiposity, which has a strong association with cognitive disorders (Kobo et al., 2019). A higher intake of processed meat was associated with obesity related to body fat distribution (Khodayari et al., 2022). It may be associated with the findings indicating that meat consumption can worsen the effect of obesity on cognitive performance.

In the microbiota sub-study analysis, the correlation between diet, gut microbiota and cognitive performance in 68 healthy women was examined. Increased Fast Food factor scores were associated with lower scores on the Episodic memory task. It was determined that fast food was a component of the WS diet. The WS diet lacks essential polyphenols and antioxidants, may be deficient in beneficial omega-3 PUFAs, and may impair mood and cognitive function (Kanoski & Davidson, 2011).

In addition, the WS diet is associated with a reduced diversity of gut microbiota (Kolodziejczyk et al., 2019), but the study found no association between Shannon diversity and the Fast Food factor. Shannon diversity was positively associated with performance on the Episodic memory task. This result is supported by another study (Canipe et al., 2021) showing that the diversity of the microbiota in the gut can influence cognitive function. Next, the *Senegalimassilia* bacteria gene was discovered to be related to Episodic task performance, but only on a tendency level.

The first hypothesis of the study was to examine the effect of unhealthy food products on cognitive performance, as well as to determine whether these effects vary according to diet type. The results confirmed that harmful foods may impair cognitive function. However, the dependence of this relationship on a particular type of diet was not confirmed. The second hypothesis was to determine whether gut microbiota can mitigate the negative impacts of unhealthy foods. The hypothesis has not been confirmed. However, gut microbiota diversity may directly influence cognitive performance.

Discussion

The purpose of this thesis was to examine the relationship between diet, gut microbiota and cognitive functioning. Starting with the diet-cognition relationship, in the first study the memory search task performance was negatively correlated with the red meat and animal fat consumption, particularly in the group of relatively older people. The high quality, white meat and fish consumption, on the other hand, were positively related to memory. Such results can be interpreted as evidence that diet may be a protective (or impeding) factor in age-related cognitive decline. In the second study the Mental Rotation task performance was negatively related to the RFM index (which may indicating metabolic adiposity) with higher Meat consumption. There was also a negative correlation between Fast Food dietary patterns and Episodic memory task performance. As to the relationship between cognitive performance and microbiota functioning the data collected in the second study revealed a significant positive correlation between microbiota diversity and the Episodic task performance. The number of *Senegalimassilia* genus was also associated with Episodic memory task, but only on a tendency level.

These findings are particularly noteworthy in the light of research demonstrating that unhealthy diet deteriorates cognitive aspects related to hippocampus, e.g. episodic memory performance (Baym et al., 2014; Hsu & Kanoski, 2014; Kaczmarczyk et al., 2013; Noble et al., 2019; Reichelt et al., 2015; Suarez et al., 2019), or spatial learning (Can et al., 2012; Page et al., 2014; Tozuka et al., 2010; White et al., 2009). Moreover, the deterioration of hippocampus caused by the WS diet may be associated with weakened blood brain barrier integrity (Kanoski et al., 2010). The WS diet increases the risk of Alzheimer's disease (Gannon et al., 2022; Grant et al., 2002; Mietelska-Porowska et al., 2022) and leads to increased incidence of obesity, dyslipidemia, and hypertension, all of which are components of the metabolic syndrome that are also associated with Alzheimer's disease (Pasinetti & Eberstein, 2008).

For both studies, dietary patterns were extracted from the FFQ food questionnaire. In the first study, patterns were generated with the PCA separately for healthy and unhealthy food products. Three dietary patterns—the HCHF food, the Meat and Animal fat (taken from the group of unhealthy dietary products), and the White meat and Fish components (obtained from the variety of healthy food products)— showed effects on cognitive functioning which were moderated by age (more pronounced in the older group). Foods with a high caloric content and the potential to increase insulin response (Castro-Acosta et al., 2017) were considered the primary source for the HCHF component in the first study. The Meat and Animal fat component was not considered to be part of the Western (WS) diet, despite the fact that consuming fried meat is a typical aspect of the WS diet. Since this component was found to be associated with the consumption of legumes, vegetables, and whole grains, I concluded that it was representative of Polish cuisine. Polish food often consists of meat, fish, lunch meat, vegetables with legumes, and nutritious whole grains. It is also worth paying attention to another elements of Polish cuisine - fish and white meat. Fish is rich in long-chain PUFAs that have beneficial effects on brain function (Spencer et al., 2017) and eating fresh lean white meat appears to have a potential beneficial effect on cardiometabolic risk factors (Damigou et al., 2022). These foods were included in the White meat and Fish component, which was linked to improved cognitive performance.

In the second study, dietary patterns were generated from all dietary items of the FFQ questionnaire. Two dietary patterns—the Meat and the Fast Food showed associations with the cognitive tasks performance. The effect of meat on MRT performance was determined by the RFM index scores of the participants. Higher Meat factor scores were associated with lower cognitive task performance in the group with higher RFM scores. However, in the non-obese group, meat consumption had no significant effect on cognitive task performance. Fast Food pattern related to a lower performance on the episodic memory task.

Meat provides the body and brain with nutrients, vitamins, and minerals (Williamson et al., 2005). Red meat contains iron (Jackson et al., 2016), and early-life iron deficiency can negatively impact the development of the hippocampus and, as a consequence, impair hippocampus-dependent memory (Cavallucci et al., 2020). Fast food dietary pattern includes highly processed carbohydrates, cookies, high-fat and high-sugar foods, excess sugar, and lower consumption of fruits and vegetables, which are considered a big part of the WS diet (Rakhra et al., 2020). The WS dietary pattern is prospectively associated with cardio-metabolic traits and the incidence of the metabolic syndrome (Lathigara et al., 2023). Moreover, the WS diet, rich in refined carbohydrates and saturated fats, is associated with weakened blood-brain barrier integrity (Kanoski et al., 2010), which is consequently associated with impaired brain function. Research showed that rats fed a high-fat diet had impaired brain metabolism and decreased cognitive functioning (Higarza et al., 2023).

Despite using different techniques to extract dietary patterns, the Meat dietary patterns were related to cognitive functioning in both studies. In the first study, the frequency of different types of meat consumption mitigated the effects of age on cognitive task performance in both positive and negative ways. Memory search sub-task was negatively associated with the Red meat and Animal fat component whereas the White meat and Fish component was positively associated with memory sub-task performance. An increase in consumption of red meat and animal fat has been associated with lower scores on the memory search subtask. White meat and fish, alternatively, had a beneficial effect of consumption frequency on memory search sub-task scores, with higher scores corresponding to more frequent consumption. Those effects were visible in the older group, in the younger group the analysis did not show a significant relationship between food components and working memory functioning. In the second study, the frequency of meat consumption was again correlated with cognitive performance, but this time this effect was modified by metabolic adiposity measured with RFM index and age. Meat consumption was found to have a significant, negative effect on the Mental Rotation task performance, but in the obese group only.

The deterioration of cognitive processes with age is widely recognized (Deary et al., 2009; Salthouse, 2009, 2011), and our study not only confirmed this finding, but also showed that consumed diet may be an important factor in impeding or improving cognition in the aged people. In a group of older individuals consumption of HCHF foods reduced their ability to multitask. However, discrepancies were observed regarding the meat consumption – it turned out that meat type (red versus white) and origin (fish, chicken or beef) is crucial when considering its impact on cognition. Meat, particularly red meat, and brain function are still the subject of research, and the results are not conclusive. Consumption of red meat has been linked to decreased attention, concentration, and information processing speed in the elderly (Granic et al., 2016; Ylilauri et al., 2022). One of the studies found that consuming less red meat was associated with cognitive benefits (Zupo et al., 2022). Other studies, however, have shown that consuming more red meat, particularly unprocessed red meat, enhances cognitive functions (Ngabirano et al., 2019; H. Zhang et al., 2021). Another aspect of the research revealed no correlation (Talebi et al., 2023). However, the technique of preparing meat for consumption appears to be of utmost importance. On the basis of the meta-analysis (Quan et al., 2022), it was determined that processed meat could be one of the most significant contributors to cognitive impairment (H. Zhang et al., 2021). It turns out that consuming 50 g of such meat per day may increase the risk of such disorders (Quan et al., 2022), and Yeh et al., (2021) calculated that each increase of 25 g of processed meat per day for 8 years increases the risk of dementia (Yeh et al., 2021).

However, according to the World Cancer Research Fund International, small amounts (no more than 500 g per week) of fresh, unprocessed red meat are recommended for consumption, among other reasons, due to its protective effect against colorectal cancer, but also due to valuable nutrients such as easily accessible protein (Formica et al., 2020; H. Zhang et al., 2020) and ingredients related to the proper functioning of the nervous system, such as vitamin B12 (Leroy et al., 2023; Manacharoen et al., 2023), zinc, and iron, which are essential elements in memory and learning processes (Suarez et al., 2019). Thus, consuming unprocessed meat may enhance cognitive performance (Ylilauri et al., 2022, p. 1). It appears that processed, oily meat impairs cognitive function (Quan et al., 2022; Ylilauri et al., 2022, p. 1). This may be due to the manner in which such meat is prepared during production procedures involving N-nitroso compounds, nitrites added as food preservatives (T. S. Allen et al., 2022). It is believed that these compounds create inflammation in the body, which is in turn linked to dementia (Quan et al., 2022). Scientists are currently inclined to believe that processed and unprocessed meat have different effects on the body's function and should therefore be regarded separately in dietary recommendations (Giromini & Givens, 2022).

In both studies, I was unable to distinguish between processed and unprocessed red meat, so all forms of red meat were grouped together. Therefore, it is conceivable that the section on processed meat contributed to the presented result. In addition, meat consumption in humans occurs in the context of an individual's entire dietary pattern, lifestyle, and physical and mental health (Johnston et al., 2023). In contrast, the relationship between the consumption of more white lean meat and fish and cognitive functions appears to be more consistent. The E-Lancet Commission's reference diet recommends consuming three times more poultry meat than red meat (Dalile et al., 2022). In a number of studies, the authors conclude that the consumption of unprocessed white meat is not associated with the risk of dementia (Yeh et al., 2021), and in the case of fish, a lower risk of cognitive impairment and dementia (Barberger-Gateau, 2002; Kalmijn et al., 2004; Talebi et al., 2023). In addition, it was discovered that a positive effect was visible with as little as 20 grams of fish per day (Nurk et al., 2007). Consuming as little as 8 g of fish per day during adolescence increases the likelihood of outperforming non-fish eaters on academic assessments (Dalile et al., 2022). Long-term consumption of fish once per week can reduce the rate of cognitive decline in the elderly by 10%, and four servings per week can delay cognitive decline by four years (Dalile et al., 2022). However, these results should be interpreted with caution due to the substantial mercury contamination of fish. A large quantity of mercury accumulates in the body as a result of their high consumption and can lead to a decline in cognitive functions (Dalile et al., 2022). The presence of polyunsaturated fatty acids (PUFA) is one of the reasons why fish has such an effect on the functioning of the nervous system. PUFAs have anti-inflammatory effects (Quan et al., 2022), as well as in the brain (Barberger-Gateau, 2002), antithrombotic properties, and are an essential component of neuronal membranes (Quan et al., 2022) and prevent the development of metabolic syndrome (Kouvari et al., 2022).

In the second study, the Meat dietary pattern was examined without differentiation into red meat, white meat, and fish. Meat consumption was associated with lower MRT performance, but only among participants with higher RFM scores. Common anthropometric indicators of adiposity include the body mass index (BMI) or the waist circumference and the waist-to-hip ratio. Current definitions of overweight and obesity are based on the body mass index (BMI), despite the fact that the BMI may not accurately reflect adipose fat mass (Suthahar et al., 2023). The RFM index is better compared to the BMI for diagnosing obesity.

RFM is one of several new anthropometric indices devised to assess the body fat distribution and total fat mass more precisely (Cichosz et al., 2022). It is more accurate than BMI for estimating body fat (Jambart, 2021) and the risk of metabolic syndrome development (Woolcott & Bergman, 2018). Metabolic syndrome is characterized by a cluster of interdependent ailments, including insulin resistance, hypertension, hyperglycemia, dyslipidemia, and abdominal obesity. It can lead to the development of type 2 diabetes and cardiovascular diseases. It also increasingly raises concerns about its association with the development of dementia and the decline of cognitive functions (Mumme et al., 2022). Obesity is associated with an increased risk of dementia because obese people are more likely to develop metabolic syndrome and insulin resistance (Manacharoen et al., 2023). RFM index was shown to be associated with developing metabolic obesity (Kobo et al., 2019).

Currently, insulin resistance and type 2 diabetes (Kouvari et al., 2022), as well as obesity (Lentoor & Myburgh, 2022), are becoming a real plague in the world. Both of these diseases are increasingly associated with the risk of dementia and cognitive decline (Kouvari et al., 2022). The functions of insulin in the CNS include glucose metabolism, modulation of neuronal function and plasticity processes, learning and memory, and regulation of energy balance (Frisardi et al., 2010; Kouvari et al., 2022). No wonder that disorders in its homeostasis can have such a huge impact on cognitive functioning. It turned out that intranasal administration of insulin to people suffering from Alzheimer’s disease had a positive effect on their cognitive performance (Hallschmid, 2021). It is not a coincidence that the term “type 3 diabetes mellitus” can be found more and more often in relation to Alzheimer’s disease (Kouvari et al., 2022).

Obesity is strongly associated with the development of cognitive disorders. The obesity epidemic has focused attention on the endocrine function of adipose tissue (Kobo et al., 2019). Adipose tissue regulates energy balance, glucose, and lipids and may contribute to diseases associated with obesity (Ahima, 2006). Adipose tissue is involved in the release of cytokines and proteins associated with low-grade chronic inflammation in the body (Frisardi et al., 2010). This chronic inflammation is associated with hypothalamic dysfunction, dysregulation of the hypothalamic-pituitary-adrenal (HPA) axis, and subsequently, mood and cognitive dysfunctions (Kouvari et al., 2022). Considering these factors, the decline in task performance among participants with a higher RFM index appears understandable. Particularly in cases where the index indicates metabolic disorders, it can be assumed that the primary type of meat consumed is processed meat. As demonstrated earlier, consumption of processed meat increases the risk of cognitive deficits.

The microbiota diversity (Shannon index) correlated with the Episodic memory task performance, which is highly significant, particularly in the context of the results associated with higher Fast Food dietary pattern scores. Lower Shannon diversity was associated with decreased performance on the Episodic memory task, and literature suggests that alterations in the composition of the gut microbiota can affect cognitive functioning (Cryan et al., 2019). Additionally, alpha-diversity was linked to gastrointestinal health and metabolic disorders. Obesity and metabolic syndromes have been linked to the lack of biodiversity (Le Chatelier et al., 2013). In addition, the Western diet was associated with decreased microbiome alpha diversity (Kolodziejczyk et al., 2019). However, in the study presented in this thesis there was no correlation between Shannon diversity and Fast Food dietary patterns. The effect of the Shannon index alone was observed, which may be an advantage of the study, because the effect of microbiota on cognitive function is mostly observed in the context of a disease or a diet.

At the level of the microbiota community, *Senegalimassilia* was discovered to be associated with the Episodic memory task on a tendency level. In addition, *Senegalimassilia* was not correlated with any of the dietary patterns. However, in the scientific literature, *Senegalimassilia* has been examined mostly in the context of healthy features (Adamberg et al., 2018). The differences in abundance of each taxon revealed that the *Senegalimassilia* gene influences episodic task performance. *Senegalimassilia* have been unfortunately poorly understood yet (Müller et al., 2020). In the context of cognitive impairment, the relationship between *Senegalimassilia* ASV and Parkinson's disease (PD) has been found in a number of studies. In contrast, several studies have observed *Senegalimassilia* gene in the context of dietary interventions for a variety of diseases, most notably metabolic syndrome.

The gut microbiota has been suggested to be a significant indicator of Parkinson’s disease (Perez-Pardo et al., 2017), and *Senegalimassilia* abundance was associated with a potential gene related to an increased risk of its development (Jiang et al., 2023.). In another study, O’Donovan et al., (2020) generated a rat brain model of the PD (O’Donovan et al., 2020). Increased physical activity protected rats from neuronal degeneration and altered gut microbiota composition, and and physically active animals had reduced *Senegalimassilia* abundance (O’Donovan et al., 2020). *Senegalimassilia* abundance was also shown to be reduced in patients with Essential tremor disorder compared to PD patients (P. Zhang et al., 2022). In addition, it is well-established that regular exercise might help reduce a cognitive decline in the metabolic syndrome (Guicciardi et al., 2019).

Senegalimassilia has been related to a number of diseases, including metabolic syndrome and obesity. Furthermore, it is well documented that metabolic syndrome and obesity have an impact on brain function, are associated with worse cognitive performance

(Kouvari et al., 2022; Yates et al., 2012), higher mortality rates (Pammer et al., 2021), and a higher risk of developing dementia (Alasantro et al., 2021).

In the presented results, it is possible that no association was found between *Senegalimassilia* counts and BMI because the participants recruited for this study were predominantly healthy and not obese. In addition, one of the objectives of this study was to determine whether certain gut bacteria can provide protection and mitigate the negative effects of eating unhealthy food products. Nonetheless, there was inadequate support for further statistical analysis, such as mediation. The results of the analysis of the differences in abundance of each taxa found the effect of *Senegalimassilia* on the cognitive task, yet only on a trend level. In addition, *Senegalimassilia* was detected in the feces of 22 individuals out of 68, which is one of the study's limitations. Additional correlation analysis of the group of 22 showed a non-significant association between the bacteria taxa and the score on the episodic task. Nonetheless, it is worth contemplating and replicating the study with these parameters on a larger sample of women.

Other research has demonstrated the significance of *Senegalimassilia* for mental health. Mairinger et al., (2023) conducted a study examining the relationship between gut microbiota and sleep quality in patients with major psychiatric disorders (major depressive, bipolar, and psychotic disorders). *Senegalimassilia* was one of the bacteria whose increased prevalence was associated with improved sleep quality (Mairinger et al., 2023). In addition, the diversity of the gut microbiome has been linked to both sleep physiology and cognition (R. P. Smith et al., 2019). In another study, Zheng et al., 2021 divided a group of depressed people based on their level of anxiety. Group with higher levels of anxiety had a lower abundance of *Senegalimassilia* than those with lower levels of anxiety (S. Zheng et al., 2021).

Number of studies indicated that increased alcohol consumption is associated with unhealthy dietary patterns (Breslow et al., 2006; Joseph et al., 2022; Kesse et al., 2001). In addition, it has been observed that with moderate and higher alcohol consumption, men and women chose various quantities of unhealthy food products, such as fast food, confectionary, soft drinks (Crovetto et al., 2022; Fawehinmi et al., 2012). The characteristics of microbiota sub-study participants showed that 36.7% of women reported drinking alcohol. The alcohol consumption was not considered during recruitment or in determining dietary patterns, which is one of the limitations of this study. However, the percentage of vegetarians and omnivores who consume alcohol was comparable. Also, another limitation of the study, in terms of interpreting dietary associations with cognition, is that there was a bias factor associated with the selection of participants for the microbiota sub-study: we selected people having extremely healthy or extremely unhealthy diet based on an index of unhealthy eating among vegetarians and omnivores. In addition, healthy individuals without chronic diseases were recruited, resulting in the formation of a distinct cohort.

Furthermore, we encountered difficulties in gathering the nutritional information because a single product category might be created with a wide variety of ingredients and preparation techniques. Vegan goods, for instance, replace animal ingredients with plant-based ones. In this regard, energy or nutritional components of the same type of product may differ from one another. Participants may interpret cheese consumption features in the same way for traditional cheese (made from animal fat) and vegan cheese (made from plant-based substitute), despite the fact that both cheeses are completely different in their nutrients or components and cannot be assumed to be the same type of food product in the traditional approach.

One additional factor that must be considered is the uncertainty regarding the applicability of the presented findings to men. It is worth noting that hormone levels, particularly estrogen in women, are also known to be influenced by the gut microbiome (Flores et al., 2012). The review by Rold et al., (2022), for example, found that several research have linked gestational diabetes mellitus with dysbiosis of the gut microbiota (Rold et al., 2022). Adolescent females with polycystic ovary syndrome had lower alpha diversity, different gut microbiome features, and a taxonomic profile in which the *Senegalimassilia* genus was less prevalent than in the control group (Garcia-Beltran et al., 2021). In addition, the differences in gut microbiota communities were also found between males and females in kidney stone disease; a lower abundance of *Senegalimassilia* was found in the female group (Zhao et al., 2021).

Conclusions

The findings presented in this thesis revealed that the frequency with which different types of foods are consumed (healthy and unhealthy dietary patterns) differently influence cognitive functioning depending on the age group. Consumption of red meat and animal fat was negatively connected with cognitive function, and this relationship was observed in the group of older participants. White meat and fish diet, on the other hand, were linked to improved memory. In the older adult group different indicators of food patterns (both positive and negative) were stronger predictors of cognitive performance. These findings support the idea that diet may play a protective (or impeding) role in age-related cognitive decline.

The Meat pattern was analyzed as a one factor in the second study, with no distinction to red meat, white meat, and fish. Before isolating dietary patterns by considering only various types of meat, I wanted to examine meat within the context of the entire diet. Higher meat consumption was associated with worse Mental Rotation task performance, but only in those participants with higher RFM scores. The frequency of meat consumption was found to moderate the cognitive consequences of metabolic obesity (measured with the RFM). Mental Rotation task scores were inversely related to age, and RFM, but not to Meat as the model's main effect. In addition, the Meat x RFM interaction effect on cognitive task performance was significant in this analysis. To visualize this interaction effect participants were split into two groups based on their RFM values. Meat consumption was associated with lower Mental Rotation task performance, but only among participants with higher RFM scores. The effect of meat eating was not observed in those with RFM scores in the average range.

Body mass index (BMI), waist circumference, and waist-hip ratio are three popular anthropometric markers of obesity. The current definitions of overweight and obesity are based on body mass index (BMI), despite the fact that BMI does not always adequately indicate fat mass (Suthahar et al., 2023). When compared to body mass index, RFM index is a better tool for diagnosing obesity. Obesity is linked to an increased risk of dementia because obese people are more likely to develop metabolic syndrome and insulin resistance (Manacharoen et al., 2023). As indicated by the elevated RFM index, metabolic adiposity is especially detrimental for cognition (Kobo et al., 2019).

The metabolic syndrome may also contribute to cognitive deterioration through insulin resistance, among other factors (Al Haj Ahmad et al., 2022). Glucose metabolism, effects on neuronal function and plasticity processes, learning and memory, and energy balance regulation are all roles of insulin in the central nervous system (Frisardi et al., 2010). Thus, disruptions in its homeostasis can have a major effect on cognitive performance. In this light, the decline in task performance in those with higher RFM index scores appears understandable, especially given that for those with scores indicating metabolic disorders, it can be assumed that the primary type of meat consumed is processed meat, which, as demonstrated in the first study, carries the risk of cognitive deficits.

The results of the microbiota sub-study revealed a correlation between Fast Food dietary patterns and Episodic memory task performance. The Fast Food pattern, which includes sweets, white flour bread, and fast food, may be related to the recently extensively researched WS diet. The WS diet is primarily made from processed foods (Weinstein et al., 2023). This type of food is distinguished by the fact that its primary components are derived from food. Moreover, it contains preservatives, and other additives that enhance the flavor, texture, and aroma. Additionally, it is high in sugar, sodium, and fat, but contains very few nutrients (Hecht et al., 2022). Consuming processed foods and increased calorie intake from processed foods is linked to a decline in general cognitive and executive function. Highly processed meat, lipids, and dairy products have been linked to a decline in cognitive performance, particularly in women and the obese (Weinstein et al., 2023). Animal and human research showed that even a short time exposure to such diet can cause cognitive impairment (Attuquayefio et al., 2017; Kanoski & Davidson, 2011). Obesity, as previously stated, is related with chronic inflammation, which affects brain function. This demonstrates that the result attained is supported by significant proof from the scientific literature.

The microbiota results showed significant positive relationship with alpha diversity (Shannon index) and the Episodic memory test. Lower Shannon diversity was associated with poor performance on the Episodic memory task, and research suggests that changes in gut microbiota composition can impair cognitive function (Cryan et al., 2019). Furthermore, the Western diet was linked to lower microbiome alpha diversity (Kolodziejczyk et al., 2019). However, no association was found between Shannon diversity and Fast Food consumption patterns. The effect of the Shannon index alone on the cognitive fucntionning was found, which could be an advantage of this study as the influence of microbiota on cognitive performance is typically examined in the context of a sickness or a specific diet. The lack of expected mediation effects of gut microbiota in the diet-cognitive performance relationship suggests that gut microbiota and dietary patterns might affect cognitive functioning through separate mechanism.

References

Adamberg, K., Adamberg, S., Ernits, K., Larionova, A., Voor, T., Jaagura, M., Visnapuu, T., & Alamäe, T. (2018). Composition and metabolism of fecal microbiota from normal and overweight children are differentially affected by melibiose, raffinose and raffinose-derived fructans. *Anaerobe*, *52*, 100–110. https://doi.org/10.1016/j.anaerobe.2018.06.009

Adan, R. A. H., van der Beek, E. M., Buitelaar, J. K., Cryan, J. F., Hebebrand, J., Higgs, S., Schellekens, H., & Dickson, S. L. (2019). Nutritional psychiatry: Towards improving mental health by what you eat. *European Neuropsychopharmacology*, *29*(12), 1321–1332. https://doi.org/10.1016/j.euroneuro.2019.10.011

Ahima, R. S. (2006). Metabolic Actions of Adipocyte Hormones: Focus on Adiponectin. *Obesity*, *14*(S2), 9S-15S. https://doi.org/10.1038/oby.2006.276

Al Haj Ahmad, R. M., Ababneh, N. A., & Al-Domi, H. A. (2022). Brain insulin resistance as a mechanistic mediator links peripheral metabolic disorders with declining cognition. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*, *16*(4), 102468. https://doi.org/10.1016/j.dsx.2022.102468

Alasantro, L. H., Hicks, T. H., Green-Krogmann, E., & Murphy, C. (2021). Metabolic syndrome and cognitive performance across the adult lifespan. *PLOS ONE*, *16*(5), e0249348. https://doi.org/10.1371/journal.pone.0249348

Allcock, L., Mantzioris, E., & Villani, A. (2022). Adherence to a Mediterranean Diet is associated with physical and cognitive health: A cross-sectional analysis of community-dwelling older Australians. *Frontiers in Public Health*, *10*. https://www.frontiersin.org/articles/10.3389/fpubh.2022.1017078

Allen, A. P., Hutch, W., Borre, Y. E., Kennedy, P. J., Temko, A., Boylan, G., Murphy, E., Cryan, J. F., Dinan, T. G., & Clarke, G. (2016). Bifidobacterium longum 1714 as a translational psychobiotic: Modulation of stress, electrophysiology and neurocognition in healthy volunteers. *Translational Psychiatry*, *6*(11), Article 11. https://doi.org/10.1038/tp.2016.191

Allen, T. S., Bhatia, H. S., Wood, A. C., Momin, S. R., & Allison, M. A. (2022). State-of-the-Art Review: Evidence on Red Meat Consumption and Hypertension Outcomes. *American Journal of Hypertension*, *35*(8), 679–687. https://doi.org/10.1093/ajh/hpac064

Anderson, M. (2001). A new method for non-parametric multivariate analysis of variance. *Austral Ecology*, *26*, 32–46. https://doi.org/10.1111/j.1442-9993.2001.01070.pp.x

Arruda, A. P., Milanski, M., Coope, A., Torsoni, A. S., Ropelle, E., Carvalho, D. P., Carvalheira, J. B., & Velloso, L. A. (2011). Low-grade hypothalamic inflammation leads to defective thermogenesis, insulin resistance, and impaired insulin secretion. *Endocrinology*, *152*(4), 1314–1326. https://doi.org/10.1210/en.2010-0659

Assan, D., Huang, Y., Mustapha, U. F., Addah, M. N., Li, G., & Chen, H. (2021). Fish Feed Intake, Feeding Behavior, and the Physiological Response of Apelin to Fasting and Refeeding. *Frontiers in Endocrinology*, *12*. https://www.frontiersin.org/articles/10.3389/fendo.2021.798903

Attuquayefio, T., Stevenson, R. J., Oaten, M. J., & Francis, H. M. (2017). A four-day Western-style dietary intervention causes reductions in hippocampal-dependent learning and memory and interoceptive sensitivity. *PLOS ONE*, *12*(2), e0172645. https://doi.org/10.1371/journal.pone.0172645

Avallone, R., Vitale, G., & Bertolotti, M. (2019). Omega-3 Fatty Acids and Neurodegenerative Diseases: New Evidence in Clinical Trials. *International Journal of Molecular Sciences*, *20*(17), Article 17. https://doi.org/10.3390/ijms20174256

Bailey, M. T., Dowd, S. E., Galley, J. D., Hufnagle, A. R., Allen, R. G., & Lyte, M. (2011). Exposure to a social stressor alters the structure of the intestinal microbiota: Implications for stressor-induced immunomodulation. *Brain, Behavior, and Immunity*, *25*(3), 397–407. https://doi.org/10.1016/j.bbi.2010.10.023

Barberger-Gateau, P. (2002). Fish, meat, and risk of dementia: Cohort study. *BMJ*, *325*(7370), 932–933. https://doi.org/10.1136/bmj.325.7370.932

Baym, C. L., Khan, N. A., Monti, J. M., Raine, L. B., Drollette, E. S., Moore, R. D., Scudder, M. R., Kramer, A. F., Hillman, C. H., & Cohen, N. J. (2014). Dietary lipids are differentially associated with hippocampal-dependent relational memory in prepubescent children1234. *The American Journal of Clinical Nutrition*, *99*(5), 1026–1032. https://doi.org/10.3945/ajcn.113.079624

Bazinet, R. P., & Layé, S. (2014). Polyunsaturated fatty acids and their metabolites in brain function and disease. *Nature Reviews. Neuroscience*, *15*(12), 771–785. https://doi.org/10.1038/nrn3820

Beaulieu, K., & Blundell, J. (2021). The Psychobiology of Hunger – A Scientific Perspective. *Topoi*, *40*(3), 565–574. https://doi.org/10.1007/s11245-020-09724-z

Beekman, T. L., Crandall, P. G., & Seo, H.-S. (2022). You Eat How You Think: A Review on the Impact of Cognitive Styles on Food Perception and Behavior. *Foods*, *11*(13), Article 13. https://doi.org/10.3390/foods11131886

Behrendt, S. (2023). *Add Standardized Regression Coefficients to Linear-Model-Objects*. https://cran.r-project.org/web/packages/lm.beta/index.html

Benelam, B. (2009). Satiation, satiety and their effects on eating behaviour. *Nutrition Bulletin*, *34*(2), 126–173. https://doi.org/10.1111/j.1467-3010.2009.01753.x

Bercik, P., Denou, E., Collins, J., Jackson, W., Lu, J., Jury, J., Deng, Y., Blennerhassett, P., Macri, J., McCoy, K. D., Verdu, E. F., & Collins, S. M. (2011). The Intestinal Microbiota Affect Central Levels of Brain-Derived Neurotropic Factor and Behavior in Mice. *Gastroenterology*, *141*(2), 599-609.e3. https://doi.org/10.1053/j.gastro.2011.04.052

Berridge, K. C. (1996). Food reward: Brain substrates of wanting and liking. *Neuroscience and Biobehavioral Reviews*, *20*(1), 1–25. https://doi.org/10.1016/0149-7634(95)00033-b

Bertelli, A., Biagi, M., Corsini, M., Baini, G., Cappellucci, G., & Miraldi, E. (2021). Polyphenols: From Theory to Practice. *Foods*, *10*(11), 2595. https://doi.org/10.3390/foods10112595

Bested, A. C., Logan, A. C., & Selhub, E. M. (2013). Intestinal microbiota, probiotics and mental health: From Metchnikoff to modern advances: part III – convergence toward clinical trials. *Gut Pathogens*, *5*(1), 4. https://doi.org/10.1186/1757-4749-5-4

Blasco, G., Moreno-Navarrete, J. M., Rivero, M., Pérez-Brocal, V., Garre-Olmo, J., Puig, J., Daunis-i-Estadella, P., Biarnés, C., Gich, J., Fernández-Aranda, F., Alberich-Bayarri, Á., Moya, A., Pedraza, S., Ricart, W., López, M., Portero-Otin, M., & Fernandez-Real, J.-M. (2017). The Gut Metagenome Changes in Parallel to Waist Circumference, Brain Iron Deposition, and Cognitive Function. *The Journal of Clinical Endocrinology & Metabolism*, *102*(8), 2962–2973. https://doi.org/10.1210/jc.2017-00133

Bloemendaal, M., Szopinska-Tokov, J., Belzer, C., Boverhoff, D., Papalini, S., Michels, F., van Hemert, S., Arias Vasquez, A., & Aarts, E. (2021). Probiotics-induced changes in gut microbial composition and its effects on cognitive performance after stress: Exploratory analyses. *Translational Psychiatry*, *11*(1), 300. https://doi.org/10.1038/s41398-021-01404-9

Bokulich, N. A., Kaehler, B. D., Rideout, J. R., Dillon, M., Bolyen, E., Knight, R., Huttley, G. A., & Gregory Caporaso, J. (2018). Optimizing taxonomic classification of marker-gene amplicon sequences with QIIME 2’s q2-feature-classifier plugin. *Microbiome*, *6*(1), 90. https://doi.org/10.1186/s40168-018-0470-z

Borriello, S. P., Hammes, W. P., Holzapfel, W., Marteau, P., Schrezenmeir, J., Vaara, M., & Valtonen, V. (2003). Safety of probiotics that contain lactobacilli or bifidobacteria. *Clinical Infectious Diseases: An Official Publication of the Infectious Diseases Society of America*, *36*(6), 775–780. https://doi.org/10.1086/368080

Bramorska, A., Zarzycka, W., Podolecka, W., Kuc, K., & Brzezicka, A. (2021). Age-Related Cognitive Decline May Be Moderated by Frequency of Specific Food Products Consumption. *Nutrients*, *13*(8), 2504. https://doi.org/10.3390/nu13082504

Bravo, J. A., Forsythe, P., Chew, M. V., Escaravage, E., Savignac, H. M., Dinan, T. G., Bienenstock, J., & Cryan, J. F. (2011). Ingestion of Lactobacillus strain regulates emotional behavior and central GABA receptor expression in a mouse via the vagus nerve. *Proceedings of the National Academy of Sciences*, *108*(38), 16050–16055. https://doi.org/10.1073/pnas.1102999108

Bray, J. R., & Curtis, J. T. (1957). An Ordination of the Upland Forest Communities of Southern Wisconsin. *Ecological Monographs*, *27*(4), 325–349. https://doi.org/10.2307/1942268

Breslow, R. A., Guenther, P. M., & Smothers, B. A. (2006). Alcohol drinking patterns and diet quality: The 1999-2000 National Health and Nutrition Examination Survey. *American Journal of Epidemiology*, *163*(4), 359–366. https://doi.org/10.1093/aje/kwj050

Brunstrom, J. M., Burn, J. F., Sell, N. R., Collingwood, J. M., Rogers, P. J., Wilkinson, L. L., Hinton, E. C., Maynard, O. M., & Ferriday, D. (2012). Episodic Memory and Appetite Regulation in Humans. *PLoS ONE*, *7*(12), e50707. https://doi.org/10.1371/journal.pone.0050707

Butler, M. J., & Eckel, L. A. (2018). Eating as a motivated behavior: Modulatory effect of high fat diets on energy homeostasis, reward processing, and neuroinflammation. *Integrative Zoology*, *13*(6), 673–686. https://doi.org/10.1111/1749-4877.12340

Calder, P. C. (2013). Omega-3 polyunsaturated fatty acids and inflammatory processes: Nutrition or pharmacology? *British Journal of Clinical Pharmacology*, *75*(3), 645–662. https://doi.org/10.1111/j.1365-2125.2012.04374.x

Callahan, B. J., McMurdie, P. J., Rosen, M. J., Han, A. W., Johnson, A. J. A., & Holmes, S. P. (2016). DADA2: High-resolution sample inference from Illumina amplicon data. *Nature Methods*, *13*(7), Article 7. https://doi.org/10.1038/nmeth.3869

Can, Ö. D., Ulupinar, E., Özkay, Ü. D., Yegin, B., & Öztürk, Y. (2012). The effect of simvastatin treatment on behavioral parameters, cognitive performance, and hippocampal morphology in rats fed a standard or a high-fat diet. *Behavioural Pharmacology*, *23*(5 and 6), 582. https://doi.org/10.1097/FBP.0b013e328356c3f2

Canipe, L. G., Sioda, M., & Cheatham, C. L. (2021). Diversity of the gut-microbiome related to cognitive behavioral outcomes in healthy older adults. *Archives of Gerontology and Geriatrics*, *96*, 104464. https://doi.org/10.1016/j.archger.2021.104464

Carabotti, M., Scirocco, A., Maselli, M. A., & Severi, C. (2015). The gut-brain axis: Interactions between enteric microbiota, central and enteric nervous systems. *Annals of Gastroenterology : Quarterly Publication of the Hellenic Society of Gastroenterology*, *28*(2), 203–209.

Carreiro, A. L., Dhillon, J., Gordon, S., Jacobs, A. G., Higgins, K. A., McArthur, B. M., Redan, B. W., Rivera, R. L., Schmidt, L. R., & Mattes, R. D. (2016). The macronutrients, appetite and energy intake. *Annual Review of Nutrition*, *36*, 73–103. https://doi.org/10.1146/annurev-nutr-121415-112624

Castro-Acosta, M. L., Stone, S. G., Mok, J. E., Mhajan, R. K., Fu, C.-I., Lenihan-Geels, G. N., Corpe, C. P., & Hall, W. L. (2017). Apple and blackcurrant polyphenol-rich drinks decrease postprandial glucose, insulin and incretin response to a high-carbohydrate meal in healthy men and women. *The Journal of Nutritional Biochemistry*, *49*, 53–62. https://doi.org/10.1016/j.jnutbio.2017.07.013

Cavallucci, V., Fidaleo, M., & Pani, G. (2020). Nutrients and neurogenesis: The emerging role of autophagy and gut microbiota. *Current Opinion in Pharmacology*, *50*, 46–52. https://doi.org/10.1016/j.coph.2019.11.004

Chen, Y., Michalak, M., & Agellon, L. B. (2018). Importance of Nutrients and Nutrient Metabolism on Human Health. *The Yale Journal of Biology and Medicine*, *91*(2), 95–103.

Ciccantelli, B., Pribic, T., Malagelada, C., Accarino, A., & Azpiroz, F. (2017). Relation between cognitive and hedonic responses to a meal. *Neurogastroenterology & Motility*, *29*(5), e13011. https://doi.org/10.1111/nmo.13011

Cichosz, S. L., Rasmussen, N. H., Vestergaard, P., & Hejlesen, O. (2022). Is predicted body-composition and relative fat mass an alternative to body-mass index and waist circumference for disease risk estimation? *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*, *16*(9), 102590. https://doi.org/10.1016/j.dsx.2022.102590

Cifuentes, L., & Acosta, A. (2022). Homeostatic regulation of food intake. *Clinics and Research in Hepatology and Gastroenterology*, *46*(2), 101794. https://doi.org/10.1016/j.clinre.2021.101794

Cole, J. H., Marioni, R. E., Harris, S. E., & Deary, I. J. (2019). Brain age and other bodily ‘ages’: Implications for neuropsychiatry. *Molecular Psychiatry*, *24*(2), Article 2. https://doi.org/10.1038/s41380-018-0098-1

Corbo, I., Marselli, G., Di Ciero, V., & Casagrande, M. (2023). The Protective Role of Cognitive Reserve in Mild Cognitive Impairment: A Systematic Review. *Journal of Clinical Medicine, 12*(5), 1759. https://doi.org/10.3390/jcm12051759

Cordner, Z. A., & Tamashiro, K. L. K. (2015). Effects of high-fat diet exposure on learning & memory. *Physiology & Behavior, 152*, 363–371. https://doi.org/10.1016/j.physbeh.2015.06.008

Costa, P., & Mccrae, R. (1992). Neo PI-R professional manual. *Psychological Assessment Resources, 396*.

Craig, C. L., Marshall, A. L., Sjöström, M., Bauman, A. E., Booth, M. L., Ainsworth, B. E., Pratt, M., Ekelund, U., Yngve, A., Sallis, J. F., & Oja, P. (2003). International Physical Activity Questionnaire: 12-Country Reliability and Validity. *Medicine & Science in Sports & Exercise, 35*(8), 1381–1395. https://doi.org/10.1249/01.MSS.0000078924.61453.FB

Crovetto, M., Valladares, M., Oñate, G., Fernández, M., Mena, F., Durán Agüero, S., & Espinoza, V. (2022). Association of weekend alcohol consumption with diet variables, body mass index, cardiovascular risk and sleep. *Human Nutrition & Metabolism, 27*, 200140. https://doi.org/10.1016/j.hnm.2022.200140

Cryan, J. F., O'Riordan, K. J., Cowan, C. S. M., Sandhu, K. V., Bastiaanssen, T. F. S., Boehme, M., Codagnone, M. G., Cussotto, S., Fulling, C., Golubeva, A. V., Guzzetta, K. E., Jaggar, M., Long-Smith, C. M., Lyte, J. M., Martin, J. A., Molinero-Perez, A., Moloney, G., Morelli, E., Morillas, E., … Dinan, T. G. (2019). The Microbiota-Gut-Brain Axis. *Physiological Reviews, 99*(4), 1877–2013. https://doi.org/10.1152/physrev.00018.2018

Cummings, D. E., & Overduin, J. (2007). Gastrointestinal regulation of food intake. *Journal of Clinical Investigation, 117*(1), 13–23. https://doi.org/10.1172/JCI30227

Dalile, B., Kim, C., Challinor, A., Geurts, L., Gibney, E. R., Galdos, M. V., La Fata, G., Layé, S., Mathers, J. C., Vauzour, D., Verkuyl, J. M., & Thuret, S. (2022). The EAT–Lancet reference diet and cognitive function across the life course. *The Lancet Planetary Health, 6*(9), e749–e759. https://doi.org/10.1016/S2542-5196(22)00123-1

Dam, S. A., Mostert, J. C., Szopinska-Tokov, J. W., Bloemendaal, M., Amato, M., & Arias-Vasquez, A. (2019). The Role of the Gut-Brain Axis in Attention-Deficit/Hyperactivity Disorder. *Gastroenterology Clinics of North America*, *48*(3), 407–431. https://doi.org/10.1016/j.gtc.2019.05.001

Damigou, E., Kosti, R. I., & Panagiotakos, D. B. (2022). White Meat Consumption and Cardiometabolic Risk Factors: A Review of Recent Prospective Cohort Studies. *Nutrients*, *14*(24), Article 24. https://doi.org/10.3390/nu14245213

Davidson, T. L., Jones, S., Roy, M., & Stevenson, R. J. (2019). The Cognitive Control of Eating and Body Weight: It's More Than What You "Think." *Frontiers in Psychology*, *10*. https://www.frontiersin.org/articles/10.3389/fpsyg.2019.00062

de Macedo, I. C., de Freitas, J. S., & da Silva Torres, I. L. (2016). The Influence of Palatable Diets in Reward System Activation: A Mini Review. *Advances in Pharmacological Sciences*, *2016*, 7238679. https://doi.org/10.1155/2016/7238679

de Wouters d'Oplinter, A., Huwart, S. J. P., Cani, P. D., & Everard, A. (2022). Gut microbes and food reward: From the gut to the brain. *Frontiers in Neuroscience*, *16*. https://www.frontiersin.org/articles/10.3389/fnins.2022.947240

de Araujo, I. E., Lin, T., Veldhuizen, M. G., & Small, D. M. (2013). Metabolic Regulation of Brain Response to Food Cues. *Current Biology*, *23*(10), 878–883. https://doi.org/10.1016/j.cub.2013.04.001

Deary, I. J., Corley, J., Gow, A. J., Harris, S. E., Houlihan, L. M., Marioni, R. E., Penke, L., Rafnsson, S. B., & Starr, J. M. (2009). Age-associated cognitive decline. *British Medical Bulletin*, *92*(1), 135–152. https://doi.org/10.1093/bmb/ldp033

Devore, E. E., Kang, J. H., Breteler, M. M. B., & Grodstein, F. (2012). Dietary intakes of berries and flavonoids in relation to cognitive decline. *Annals of Neurology*, *72*(1), 135–143. https://doi.org/10.1002/ana.23594

Dinan, T. G., & Cryan, J. F. (2012). Regulation of the stress response by the gut microbiota: Implications for psychoneuroendocrinology. *Psychoneuroendocrinology*, *37*(9), 1369–1378. https://doi.org/10.1016/j.psyneuen.2012.03.007

Dinan, T. G., Stilling, R. M., Stanton, C., & Cryan, J. F. (2015). Collective unconscious: How gut microbes shape human behavior. *Journal of Psychiatric Research*, *63*, 1–9. https://doi.org/10.1016/j.jpsychires.2015.02.021

Egecioglu, E., Skibicka, K. P., Hansson, C., Alvarez-Crespo, M., Friberg, P. A., Jerlhag, E., Engel, J. A., & Dickson, S. L. (2011). Hedonic and incentive signals for body weight control. *Reviews in Endocrine and Metabolic Disorders*, *12*(3), 141–151. https://doi.org/10.1007/s11154-011-9166-4

Elsmore, T. F. (1994). SYNWORK1: A PC-based tool for assessment of performance in a simulated work environment. *Behavior Research Methods, Instruments, & Computers*, *26*(4), 421–426. https://doi.org/10.3758/BF03204659

Fawehinmi, T. O., Ilomäki, J., Voutilainen, S., & Kauhanen, J. (2012). Alcohol Consumption and Dietary Patterns: The FinDrink Study. *PLoS ONE*, *7*(6), e38607. https://doi.org/10.1371/journal.pone.0038607

Féart, C., Samieri, C., & Barberger-Gateau, P. (2010). Mediterranean diet and cognitive function in older adults. *Current Opinion in Clinical Nutrition and Metabolic Care*, *13*(1), 14–18. https://doi.org/10.1097/MCO.0b013e3283331fe4

Ferdinand, N. K., & Czernochowski, D. (2018). Motivational Influences on Performance Monitoring and Cognitive Control Across the Adult Lifespan. *Frontiers in Psychology*, *9*. https://www.frontiersin.org/articles/10.3389/fpsyg.2018.01018

Fernandez-Real, J.-M., Serino, M., Blasco, G., Puig, J., Daunis-i-Estadella, J., Ricart, W., Burcelin, R., Fernández-Aranda, F., & Portero-Otin, M. (2015). Gut Microbiota Interacts With Brain Microstructure and Function. *The Journal of Clinical Endocrinology & Metabolism*, *100*(12), 4505–4513. https://doi.org/10.1210/jc.2015-3076

Fijan, S. (2014). Microorganisms with Claimed Probiotic Properties: An Overview of Recent Literature. *International Journal of Environmental Research and Public Health*, *11*(5), 4745–4767. https://doi.org/10.3390/ijerph110504745

Fisk, J. E., & Sharp, C. A. (2004). Age-related impairment in executive functioning: Updating, inhibition, shifting, and access. *Journal of Clinical and Experimental Neuropsychology*, *26*(7), 874–890. https://doi.org/10.1080/13803390490510680

Flores, R., Shi, J., Fuhrman, B., Xu, X., Veenstra, T. D., Gail, M. H., Gajer, P., Ravel, J., & Goedert, J. J. (2012). Fecal microbial determinants of fecal and systemic estrogens and estrogen metabolites: A cross-sectional study. *Journal of Translational Medicine*, *10*(1), 253. https://doi.org/10.1186/1479-5876-10-253

Formica, M. B., Gianoudis, J., Nowson, C. A., O’Connell, S. L., Milte, C., Ellis, K. A., & Daly, R. M. (2020). Effect of lean red meat combined with a multicomponent exercise program on muscle and cognitive function in older adults: A 6-month randomized controlled trial. *The American Journal of Clinical Nutrition*, *112*(1), 113–128. https://doi.org/10.1093/ajcn/nqaa104

Forsythe, P., Kunze, W., & Bienenstock, J. (2016). Moody microbes or fecal phrenology: What do we know about the microbiota-gut-brain axis? *BMC Medicine*, *14*(1), 58, s12916-016-0604–0608. https://doi.org/10.1186/s12916-016-0604-8

Fox, J., & Adrian, D. (2022). Polycor R Package Scholar & Citation Profiles. *R Package Scholars and Citations*. https://scholar.rpkg.net

Francis, H., & Stevenson, R. (2013a). The longer-term impacts of Western diet on human cognition and the brain. *Appetite*, *63*, 119–128. https://doi.org/10.1016/j.appet.2012.12.018

Francis, H., & Stevenson, R. (2013b). Validity and test–retest reliability of a short dietary questionnaire to assess intake of saturated fat and free sugars: A preliminary study. *Journal of Human Nutrition and Dietetics*, *26*(3), 234–242. https://doi.org/10.1111/jhn.12008

Frisardi, V., Solfrizzi, V., Seripa, D., Capurso, C., Santamato, A., Sancarlo, D., Vendemiale, G., Pilotto, A., & Panza, F. (2010). Metabolic-cognitive syndrome: A cross-talk between metabolic syndrome and Alzheimer’s disease. *Ageing Research Reviews*, *9*(4), 399–417. https://doi.org/10.1016/j.arr.2010.04.007

Gannon, O. J., Robison, L. S., Salinero, A. E., Abi-Ghanem, C., Mansour, F. M., Kelly, R. D., Tyagi, A., Brawley, R. R., Ogg, J. D., & Zuloaga, K. L. (2022). High-fat diet exacerbates cognitive decline in mouse models of Alzheimer’s disease and mixed dementia in a sex-dependent manner. *Journal of Neuroinflammation*, *19*(1), 110. https://doi.org/10.1186/s12974-022-02466-2

Garcia-Beltran, C., Malpique, R., Carbonetto, B., González-Torres, P., Henares, D., Brotons, P., Muñoz-Almagro, C., López-Bermejo, A., de Zegher, F., & Ibáñez, L. (2021). Gut microbiota in adolescent girls with polycystic ovary syndrome: Effects of randomized treatments. *Pediatric Obesity*, *16*(4), e12734. https://doi.org/10.1111/ijpo.12734

García-Casares, N., Gallego Fuentes, P., Barbancho, M. Á., López-Gigosos, R., García-Rodríguez, A., & Gutiérrez-Bedmar, M. (2021). Alzheimer’s Disease, Mild Cognitive Impairment and Mediterranean Diet. A Systematic Review and Dose-Response Meta-Analysis. *Journal of Clinical Medicine*, *10*(20), 4642. https://doi.org/10.3390/jcm10204642

Gareau, M. G., Wine, E., Rodrigues, D. M., Cho, J. H., Whary, M. T., Philpott, D. J., MacQueen, G., & Sherman, P. M. (2011). Bacterial infection causes stress-induced memory dysfunction in mice. *Gut*, *60*(3), 307–317. https://doi.org/10.1136/gut.2009.202515

Gautron, L., Elmquist, J. K., & Williams, K. W. (2015). Neural Control of Energy Balance: Translating Circuits to Therapies. *Cell*, *161*(1), 133–145. https://doi.org/10.1016/j.cell.2015.02.023

Gilliland, S. E. (1990). Health and nutritional benefits from lactic acid bacteria. *FEMS Microbiology Reviews*, *7*(1–2), 175–188. https://doi.org/10.1111/j.1574-6968.1990.tb04887.x

Giromini, C., & Givens, D. I. (2022). Benefits and Risks Associated with Meat Consumption during Key Life Processes and in Relation to the Risk of Chronic Diseases. *Foods*, *11*(14), Article 14. https://doi.org/10.3390/foods11142063

Granic, A., Davies, K., Adamson, A., Kirkwood, T., Hill, T. R., Siervo, M., Mathers, J. C., & Jagger, C. (2016). Dietary Patterns High in Red Meat, Potato, Gravy, and Butter Are Associated with Poor Cognitive Functioning but Not with Rate of Cognitive Decline in Very Old Adults1234. *The Journal of Nutrition*, *146*(2), 265–274. https://doi.org/10.3945/jn.115.216952

Grant, W. B., Campbell, A., Itzhaki, R. F., & Savory, J. (2002). The significance of environmental factors in the etiology of Alzheimer's disease. *Journal of Alzheimer's Disease: JAD*, *4*(3), 179–189. https://doi.org/10.3233/jad-2002-4308

Grenham, S., Clarke, G., Cryan, J., & Dinan, T. (2011). Brain–Gut–Microbe Communication in Health and Disease. *Frontiers in Physiology*, *2*. https://www.frontiersin.org/articles/10.3389/fphys.2011.00094

Grossman, B. M., Cc, A., Jk, H., & Rj, M. (1994). Effects of a fat substitute, sucrose polyester, on food intake, body composition, and serum factors in lean and obese Zucker rats. *Obesity Research*, *2*(3). https://doi.org/10.1002/j.1550-8528.1994.tb00057.x

Grünblatt, E., Bartl, J., & Riederer, P. (2011). The link between iron, metabolic syndrome, and Alzheimer's disease. *Journal of Neural Transmission*, *118*(3), 371–379. https://doi.org/10.1007/s00702-010-0426-3

Guicciardi, M., Crisafulli, A., Doneddu, A., Fadda, D., & Lecis, R. (2019). Effects of Metabolic Syndrome on Cognitive Performance of Adults During Exercise. *Frontiers in Psychology*, *10*. https://www.frontiersin.org/articles/10.3389/fpsyg.2019.01845

Hajishafiee, M., Bitarafan, V., & Feinle-Bisset, C. (2019). Gastrointestinal Sensing of Meal-Related Signals in Humans, and Dysregulations in Eating-Related Disorders. *Nutrients*, *11*(6), 1298. https://doi.org/10.3390/nu11061298

Hallschmid, M. (2021). Intranasal Insulin for Alzheimer's Disease. *CNS Drugs*, *35*(1), 21–37. https://doi.org/10.1007/s40263-020-00781-x

Han, L., & Jia, J. (2022). Alcohol consumption, poor lifestyle choices, and air pollution worsen cognitive function in seniors: A cohort study in China. *Environmental Science and Pollution Research*, *29*(18), 26877–26888. https://doi.org/10.1007/s11356-021-17891-8

Harada, C. N., Natelson Love, M. C., & Triebel, K. (2013). Normal Cognitive Aging. *Clinics in Geriatric Medicine*, *29*(4), 737–752. https://doi.org/10.1016/j.cger.2013.07.002

Harvey, P. D. (2019). Domains of cognition and their assessment. *Dialogues in Clinical Neuroscience*, *21*(3), 227–237. https://doi.org/10.31887/DCNS.2019.21.3/pharvey

Hashemi, R., Vahabi, Z., Rasekhi, H., Shiraseb, F., & Amini, M. (2023). Dietary patterns and the risk of Alzheimer's disease in an elderly Iranian population: A case–control study. *Journal of Health, Population and Nutrition*, *42*(1), 56. https://doi.org/10.1186/s41043-023-00398-y

Hassevoort, K. M., Lin, A. S., Khan, N. A., Hillman, C. H., & Cohen, N. J. (2020). Added sugar and dietary fiber consumption are associated with creativity in preadolescent children. *Nutritional Neuroscience*, *23*(10), 791–802. https://doi.org/10.1080/1028415X.2018.1558003

Hecht, E. M., Rabil, A., Martinez Steele, E., Abrams, G. A., Ware, D., Landy, D. C., & Hennekens, C. H. (2022). Cross-sectional examination of ultra-processed food consumption and adverse mental health symptoms. *Public Health Nutrition*, *25*(11), 3225–3234. https://doi.org/10.1017/S1368980022001586

Higarza, S. G., Arboleya, S., Arias, J. L., Gueimonde, M., & Arias, N. (2023). Akkermansia muciniphila and environmental enrichment reverse cognitive impairment associated with high-fat high-cholesterol consumption in rats. *Gut Microbes*, *13*(1), 1880240. https://doi.org/10.1080/19490976.2021.1880240

Higgs, S. (2002). Memory for recent eating and its influence on subsequent food intake. *Appetite*, *39*(2), 159–166. https://doi.org/10.1006/appe.2002.0500

Higgs, S., Spetter, M. S., Thomas, J. M., Rotshtein, P., Lee, M., Hallschmid, M., & Dourish, C. T. (2017). Interactions between metabolic, reward and cognitive processes in appetite control: Implications for novel weight management therapies. *Journal of Psychopharmacology (Oxford, England)*, *31*(11), 1460–1474. https://doi.org/10.1177/0269881117736917

Higgs, S., & Thomas, J. (2016). Social influences on eating. *Current Opinion in Behavioral Sciences*, *9*, 1–6. https://doi.org/10.1016/j.cobeha.2015.10.005

Hopkins, M., Beaulieu, K., Gibbons, C., Halford, J. C. G., Blundell, J., Stubbs, J., & Finlayson, G. (2000). The Control of Food Intake in Humans. In K. R. Feingold, B. Anawalt, M. R. Blackman, A. Boyce, G. Chrousos, E. Corpas, W. W. de Herder, K. Dhatariya, K. Dungan, J. Hofland, S. Kalra, G. Kaltsas, N. Kapoor, C. Koch, P. Kopp, M. Korbonits, C. S. Kovacs, W. Kuohung, B. Laferrère, … D. P. Wilson (Eds.), *Endotext*. MDText.com, Inc. http://www.ncbi.nlm.nih.gov/books/NBK278931/

Hsu, T. M., & Kanoski, S. E. (2014). Blood-brain barrier disruption: Mechanistic links between Western diet consumption and dementia. *Frontiers in Aging Neuroscience*, *6*, 88. https://doi.org/10.3389/fnagi.2014.00088

Huhn, S., Kharabian Masouleh, S., Stumvoll, M., Villringer, A., & Witte, A. V. (2015). Components of a Mediterranean diet and their impact on cognitive functions in aging. *Frontiers in Aging Neuroscience*, *7*, 132. https://doi.org/10.3389/fnagi.2015.00132

Jackson, J., Williams, R., McEvoy, M., MacDonald-Wicks, L., & Patterson, A. (2016). Is Higher Consumption of Animal Flesh Foods Associated with Better Iron Status among Adults in Developed Countries? A Systematic Review. *Nutrients*, *8*(2), 89. https://doi.org/10.3390/nu8020089

Jambart, I. (2021). Relative Fat Mass, a new tool for measuring obesity, could predict the complications of type 2 diabetes. *Endocrinology and Disorders*, *5*(3), 01–08. https://doi.org/10.31579/2640-1045/074

Janssen, P., Vanden Berghe, P., Verschueren, S., Lehmann, A., Depoortere, I., & Tack, J. (2011). Review article: The role of gastric motility in the control of food intake. *Alimentary Pharmacology & Therapeutics*, *33*(8), 880–894. https://doi.org/10.1111/j.1365-2036.2011.04609.x

Jeżewska-Zychowicz, M., J., G., Wadolowska, L., J., C., Galiński, G., A., K.-D., Roszkowski, W., Wawrzyniak, A., Przybyłowicz, K., Stasiewicz, B., Hawrysz, I., Slowinska, M., & Niedzwiedzka, E. (2014). *Kwestionariusz do badania poglądów i zwyczajów żywieniowych oraz procedura opracowania danych*. https://doi.org/10.13140/2.1.3207.7125

Jiang, L., Li, J., Tang, B., & Guo, J. (n.d.). Associations between gut microbiota and Parkinson disease: A bidirectional Mendelian randomization analysis. *European Journal of Neurology*, *n/a*(n/a). https://doi.org/10.1111/ene.15848

Jiménez-Murcia, S., Agüera, Z., Paslakis, G., Munguia, L., Granero, R., Sánchez-González, J., Sánchez, I., Riesco, N., Gearhardt, A. N., Dieguez, C., Fazia, G., Segura-García, C., Baenas, I., Menchón, J. M., & Fernández-Aranda, F. (2019). Food Addiction in Eating Disorders and Obesity: Analysis of Clusters and Implications for Treatment. *Nutrients*, *11*(11), 2633. https://doi.org/10.3390/nu11112633

Johnston, B., De Smet, S., Leroy, F., Mente, A., & Stanton, A. (2023). Non-communicable disease risk associated with red and processed meat consumption-magnitude, certainty, and contextuality of risk? *Animal Frontiers: The Review Magazine of Animal Agriculture*, *13*(2), 19–27. https://doi.org/10.1093/af/vfac095

Joseph, P. V., Zhou, Y., Brooks, B., McDuffie, C., Agarwal, K., & Chao, A. M. (2022). Relationships among Alcohol Drinking Patterns, Macronutrient Composition, and Caloric Intake: National Health and Nutrition Examination Survey 2017–2018. *Alcohol and Alcoholism*, *57*(5), 559–565. https://doi.org/10.1093/alcalc/agac009

Kaczmarczyk, M. M., Machaj, A. S., Chiu, G. S., Lawson, M. A., Gainey, S. J., York, J. M., Meling, D. D., Martin, S. A., Kwakwa, K. A., Newman, A. F., Woods, J. A., Kelley, K. W., Wang, Y., Miller, M. J., & Freund, G. G. (2013). Methylphenidate prevents high-fat diet (HFD)-induced learning/memory impairment in juvenile mice. *Psychoneuroendocrinology*, *38*(9), 1553–1564. https://doi.org/10.1016/j.psyneuen.2013.01.004

Kalmijn, S., van Boxtel, M. P. J., Ocke, M., Verschuren, W. M. M., Kromhout, D., & Launer, L. J. (2004). Dietary intake of fatty acids and fish in relation to cognitive performance at middle age. *Neurology*, *62*(2), 275–280. https://doi.org/10.1212/01.WNL.0000103860.75218.A5

Kanoski, S. E., & Davidson, T. L. (2011). Western diet consumption and cognitive impairment: Links to hippocampal dysfunction and obesity. *Physiology & Behavior*, *103*(1), 59–68. https://doi.org/10.1016/j.physbeh.2010.12.003

Kanoski, S. E., Zhang, Y., Zheng, W., & Davidson, T. L. (2010). The Effects of a High-Energy Diet on Hippocampal Function and Blood-Brain Barrier Integrity in the Rat. *Journal of Alzheimer's Disease*, *21*(1), 207–219. https://doi.org/10.3233/JAD-2010-091414

Katoh, K., Misawa, K., Kuma, K., & Miyata, T. (2002). MAFFT: A novel method for rapid multiple sequence alignment based on fast Fourier transform. *Nucleic Acids Research*, *30*(14), 3059–3066. https://doi.org/10.1093/nar/gkf436

Katonova, A., Sheardova, K., Amlerova, J., Angelucci, F., & Hort, J. (2022). Effect of a Vegan Diet on Alzheimer's Disease. *International Journal of Molecular Sciences*, *23*(23), Article 23. https://doi.org/10.3390/ijms232314924

Kenny, P. J. (2011). Reward Mechanisms in Obesity: New Insights and Future Directions. *Neuron*, *69*(4), 664–679. https://doi.org/10.1016/j.neuron.2011.02.016

Kers, J. G., & Saccenti, E. (2022). The Power of Microbiome Studies: Some Considerations on Which Alpha and Beta Metrics to Use and How to Report Results. *Frontiers in Microbiology*, *12*, 796025. https://doi.org/10.3389/fmicb.2021.796025

Kesse, E., Clavel-Chapelon, F., Slimani, N., van Liere, M., & E3N Group. (2001). Do eating habits differ according to alcohol consumption? Results of a study of the French cohort of the European Prospective Investigation into Cancer and Nutrition (E3N-EPIC). *The American Journal of Clinical Nutrition*, *74*(3), 322–327. https://doi.org/10.1093/ajcn/74.3.322

Khodayari, S., Sadeghi, O., Safabakhsh, M., & Mozaffari-Khosravi, H. (2022). Meat consumption and the risk of general and central obesity: The Shahedieh study. *BMC Research Notes*, *15*(1), 339. https://doi.org/10.1186/s13104-022-06235-5

Kim, K.-S., Seeley, R. J., & Sandoval, D. A. (2018). Signalling from the periphery to the brain that regulates energy homeostasis. *Nature Reviews. Neuroscience*, *19*(4), 185–196. https://doi.org/10.1038/nrn.2018.8

Kobo, O., Leiba, R., Avizohar, O., & Karban, A. (2019). Relative fat mass (RFM) as abdominal obesity criterion for metabolic syndrome. *European Journal of Internal Medicine*, *63*, e9–e11. https://doi.org/10.1016/j.ejim.2019.03.002

Kok, C. R., & Hutkins, R. (2018). Yogurt and other fermented foods as sources of health-promoting bacteria. *Nutrition Reviews*, *76*(Supplement_1), 4–15. https://doi.org/10.1093/nutrit/nuy056

Kolodziejczyk, A. A., Zheng, D., & Elinav, E. (2019). Diet–microbiota interactions and personalized nutrition. *Nature Reviews Microbiology*, *17*(12), 742–753. https://doi.org/10.1038/s41579-019-0256-8

Kouvari, M., D'Cunha, N. M., Travica, N., Sergi, D., Zec, M., Marx, W., & Naumovski, N. (2022). Metabolic Syndrome, Cognitive Impairment and the Role of Diet: A Narrative Review. *Nutrients*, *14*(2), Article 2. https://doi.org/10.3390/nu14020333

Kumar, M., Srivastava, S., & Muhammad, T. (2022). Relationship between physical activity and cognitive functioning among older Indian adults. *Scientific Reports*, *12*(1), Article 1. https://doi.org/10.1038/s41598-022-06725-3

Lamport, D. (2012). The effects of flavonoid and other polyphenol consumption on cognitive function: A systematic review of human experimental and epidemiological studies. *Nutrtion and Aging*, *1*, 5–25. https://doi.org/10.3233/NUA-2012-0002

Lathigara, D., Kaushal, D., & Wilson, R. B. (2023). Molecular Mechanisms of Western Diet-Induced Obesity and Obesity-Related Carcinogenesis—A Narrative Review. *Metabolites*, *13*(5), Article 5. https://doi.org/10.3390/metabo13050675

Laveriano-Santos, E. P., Arancibia-Riveros, C., Tresserra-Rimbau, A., Castro-Barquero, S., Ruiz-León, A. M., Estruch, R., Casas, R., Bodega, P., de Miguel, M., de Cos-Gandoy, A., Martínez-Gómez, J., Rodríguez, C., Santos-Beneit, G., Fernández-Alvira, J. M., Fernández-Jiménez, R., & Lamuela-Raventós, R. M. (2022). Flavonoid Intake From Cocoa-Based Products and Adiposity Parameters in Adolescents in Spain. *Frontiers in Nutrition*, *9*. https://www.frontiersin.org/articles/10.3389/fnut.2022.931171

Le Chatelier, E., Nielsen, T., Qin, J., Prifti, E., Hildebrand, F., Falony, G., Almeida, M., Arumugam, M., Batto, J.-M., Kennedy, S., Leonard, P., Li, J., Burgdorf, K., Grarup, N., Jørgensen, T., Brandslund, I., Nielsen, H. B., Juncker, A. S., Bertalan, M., … Pedersen, O. (2013). Richness of human gut microbiome correlates with metabolic markers. *Nature*, *500*(7464), Article 7464. https://doi.org/10.1038/nature12506

Lentoor, A. G., & Myburgh, L. (2022). Correlation between Body Mass Index (BMI) and Performance on the Montreal Cognitive Assessment (MoCA) in a Cohort of Adult Women in South Africa. *Behavioural Neurology*, *2022*, e8994793. https://doi.org/10.1155/2022/8994793

Leo Lahti, Sudarshan Shetty et al. (2017). *Tools for microbiome analysis in R. Version. URL: http://microbiome.github.com/microbiome*.

Leroy, F., Smith, N. W., Adesogan, A. T., Beal, T., Iannotti, L., Moughan, P. J., & Mann, N. (2023). The role of meat in the human diet: Evolutionary aspects and nutritional value. *Animal Frontiers*, *13*(2), 11–18. https://doi.org/10.1093/af/vfac093

Li, J., An, R., Zhang, Y., Li, X., & Wang, S. (2012). Correlations of macronutrient-induced functional magnetic resonance imaging signal changes in human brain and gut hormone responses. *The American Journal of Clinical Nutrition*, *96*(2), 275–282. https://doi.org/10.3945/ajcn.112.037440

Liu, D., Hu, H., Hong, Y., Xiao, Q., & Tu, J. (2023). Sugar Beverage Habitation Relieves Chronic Stress-Induced Anxiety-like Behavior but Elicits Compulsive Eating Phenotype via vLSGAD2 Neurons. *International Journal of Molecular Sciences*, *24*(1), Article 1. https://doi.org/10.3390/ijms24010661

Livovsky, D. M., Pribic, T., & Azpiroz, F. (2020). Food, Eating, and the Gastrointestinal Tract. *Nutrients*, *12*(4), 986. https://doi.org/10.3390/nu12040986

Lobionda, S., Sittipo, P., Kwon, H. Y., & Lee, Y. K. (2019). The Role of Gut Microbiota in Intestinal Inflammation with Respect to Diet and Extrinsic Stressors. *Microorganisms*, *7*(8), 271. https://doi.org/10.3390/microorganisms7080271

Loughrey, D. G., Lavecchia, S., Brennan, S., Lawlor, B. A., & Kelly, M. E. (2017). The Impact of the Mediterranean Diet on the Cognitive Functioning of Healthy Older Adults: A Systematic Review and Meta-Analysis. *Advances in Nutrition*, *8*(4), 571–586. https://doi.org/10.3945/an.117.015495

Lucassen, P. J., Meerlo, P., Naylor, A. S., van Dam, A. M., Dayer, A. G., Fuchs, E., Oomen, C. A., & Czéh, B. (2010). Regulation of adult neurogenesis by stress, sleep disruption, exercise and inflammation: Implications for depression and antidepressant action. *European Neuropsychopharmacology: The Journal of the European College of Neuropsychopharmacology*, *20*(1), 1–17. https://doi.org/10.1016/j.euroneuro.2009.08.003

Lüdecke, D. (2023). *sjPlot: Data Visualization for Statistics in Social Science.* https://CRAN.R-project.org/package=sjPlot

Lutter, M., & Nestler, E. J. (2009). Homeostatic and Hedonic Signals Interact in the Regulation of Food Intake. *The Journal of Nutrition*, *139*(3), 629–632. https://doi.org/10.3945/jn.108.097618

Lyte, M. (2014). Microbial endocrinology and the microbiota-gut-brain axis. *Advances in Experimental Medicine and Biology*, *817*, 3–24. https://doi.org/10.1007/978-1-4939-0897-4_1

Lyte, M., & Cryan, J. F. (Eds.). (2014). *Microbial Endocrinology: The Microbiota-Gut-Brain Axis in Health and Disease* (Vol. 817). Springer New York. https://doi.org/10.1007/978-1-4939-0897-4

Macfarlane, S., & Macfarlane, G. T. (2003). Regulation of short-chain fatty acid production. *Proceedings of the Nutrition Society*, *62*(1), 67–72. https://doi.org/10.1079/PNS2002207

Madore, C., Leyrolle, Q., Morel, L., Rossitto, M., Greenhalgh, A. D., Delpech, J. C., Martinat, M., Bosch-Bouju, C., Bourel, J., Rani, B., Lacabanne, C., Thomazeau, A., Hopperton, K. E., Beccari, S., Sere, A., Aubert, A., De Smedt-Peyrusse, V., Lecours, C., Bisht, K., … Layé, S. (2020). Essential omega-3 fatty acids tune microglial phagocytosis of synaptic elements in the mouse developing brain. *Nature Communications, 11*(1), Article 1. https://doi.org/10.1038/s41467-020-19861-z

Mairinger, M., Maget, A., Wagner-Skacel, J., Mörkl, S., Dalkner, N., Hellinger, T., Birner, A., Fellendorf, F. T., Platzer, M., Kreuzer, K., Queissner, R., Reininghaus, B., Lenger, M., Fabisch, K., Fitz, W., Kohlhammer-Dohr, A., Krammer, A., Holl, A. K., Painold, A., …

Bengesser, S. (2023). Gut Microbiome Composition and Its Association with Sleep in Major Psychiatric Disorders. *Neuropsychobiology*, 1–14. https://doi.org/10.1159/000530386

Malagelada, C., Accarino, A., Molne, L., Mendez, S., Campos, E., Gonzalez, A., Malagelada, J. R., & Azpiroz, F. (2015). Digestive, cognitive and hedonic responses to a meal. *Neurogastroenterology & Motility*, *27*(3), 389–396. https://doi.org/10.1111/nmo.12504

Malagelada, C., Barba, I., Accarino, A., Molne, L., Mendez, S., Campos, E., Gonzalez, A., Alonso-Cotoner, C., Santos, J., Malagelada, J.-R., & Azpiroz, F. (2016). Cognitive and hedonic responses to meal ingestion correlate with changes in circulating metabolites. *Neurogastroenterology & Motility*, *28*(12), 1806–1814. https://doi.org/10.1111/nmo.12879

Maljaars, J., Peters, H. P. F., & Masclee, A. M. (2007). Review article: The gastrointestinal tract: neuroendocrine regulation of satiety and food intake. *Alimentary Pharmacology & Therapeutics*, *26*(s2), 241–250. https://doi.org/10.1111/j.1365-2036.2007.03550.x

Mallick, H., Rahnavard, A., McIver, L. J., Ma, S., Zhang, Y., Nguyen, L. H., Tickle, T. L., Weingart, G., Ren, B., Schwager, E. H., Chatterjee, S., Thompson, K. N., Wilkinson, J. E., Subramanian, A., Lu, Y., Waldron, L., Paulson, J. N., Franzosa, E. A., Bravo, H. C., & Huttenhower, C. (2021). Multivariable association discovery in population-scale meta-omics studies. *PLOS Computational Biology*, *17*(11), e1009442. https://doi.org/10.1371/journal.pcbi.1009442

Manacharoen, A., Jayanama, K., Ruangritchankul, S., Vathesatogkit, P., Sritara, P., & Warodomwichit, D. (2023). Association of body mass index and dietary intake with mild cognitive impairment and dementia: A retrospective cohort study. *BMC Geriatrics*, *23*(1), 3. https://doi.org/10.1186/s12877-022-03700-5

Manderino, L., Carroll, I., Azcarate-Peril, M. A., Rochette, A., Heinberg, L., Peat, C., Steffen, K., Mitchell, J., & Gunstad, J. (2017). Preliminary Evidence for an Association Between the Composition of the Gut Microbiome and Cognitive Function in Neurologically Healthy Older Adults. *Journal of the International Neuropsychological Society: JINS*, *23*(8), 700–705. https://doi.org/10.1017/S1355617717000492

Mao, X., Chen, C., Xun, P., Daviglus, M. L., Steffen, L. M., Jacobs, D. R., Van Horn, L., Sidney, S., Zhu, N., Qin, B., & He, K. (2019). Intake of Vegetables and Fruits Through Young Adulthood Is Associated with Better Cognitive Function in Midlife in the US General Population. *The Journal of Nutrition*, *149*(8), 1424–1433. https://doi.org/10.1093/jn/nxz076

Marques, C., Fernandes, I., Meireles, M., Faria, A., Spencer, J. P. E., Mateus, N., & Calhau, C. (2018). Gut microbiota modulation accounts for the neuroprotective properties of anthocyanins. *Scientific Reports*, *8*(1), Article 1. https://doi.org/10.1038/s41598-018-29744-5

Martínez-González, M. A., Gea, A., & Ruiz-Canela, M. (2019). The Mediterranean Diet and Cardiovascular Health. *Circulation Research*, *124*(5), 779–798. https://doi.org/10.1161/CIRCRESAHA.118.313348

Martín-Peláez, S., Fito, M., & Castaner, O. (2020). Mediterranean Diet Effects on Type 2 Diabetes Prevention, Disease Progression, and Related Mechanisms. A Review. *Nutrients*, *12*(8), 2236. https://doi.org/10.3390/nu12082236

Matthews, C. E., George, S. M., Moore, S. C., Bowles, H. R., Blair, A., Park, Y., Troiano, R. P., Hollenbeck, A., & Schatzkin, A. (2012). Amount of time spent in sedentary behaviors and cause-specific mortality in US adults123. *The American Journal of Clinical Nutrition*, *95*(2), 437–445. https://doi.org/10.3945/ajcn.111.019620

Matthews, G., Jones, D. M., & Chamberlain, A. G. (1990). Refining the measurement of mood: The UWIST Mood Adjective Checklist. *British Journal of Psychology*, *81*(1), 17–42. https://doi.org/10.1111/j.2044-8295.1990.tb02343.x

McCrickerd, K., & Forde, C. G. (2016). Sensory influences on food intake control: Moving beyond palatability. *Obesity Reviews*, *17*(1), 18–29. https://doi.org/10.1111/obr.12340

McMurdie, P. J., & Holmes, S. (2013). phyloseq: An R Package for Reproducible Interactive Analysis and Graphics of Microbiome Census Data. *PLOS ONE*, *8*(4), e61217. https://doi.org/10.1371/journal.pone.0061217

McNab, F., Zeidman, P., Rutledge, R. B., Smittenaar, P., Brown, H. R., Adams, R. A., & Dolan, R. J. (2015). Age-related changes in working memory and the ability to ignore distraction.

Proceedings of the National Academy of Sciences of the United States of America, *112*(20), 6515–6518. https://doi.org/10.1073/pnas.1504162112

Michielsen, H. J., De Vries, J., & Van Heck, G. L. (2003). Psychometric qualities of a brief self-rated fatigue measure: The Fatigue Assessment Scale. *Journal of Psychosomatic Research*, *54*(4), 345–352. https://doi.org/10.1016/S0022-3999(02)00392-6

Mietelska-Porowska, A., Domańska, J., Want, A., Więckowska-Gacek, A., Chutorański, D., Koperski, M., & Wojda, U. (2022). Induction of Brain Insulin Resistance and Alzheimer's Molecular Changes by Western Diet. *International Journal of Molecular Sciences*, *23*(9), Article 9. https://doi.org/10.3390/ijms23094744

Milanski, M., Degasperi, G., Coope, A., Morari, J., Denis, R., Cintra, D. E., Tsukumo, D. M. L., Anhe, G., Amaral, M. E., Takahashi, H. K., Curi, R., Oliveira, H. C., Carvalheira, J. B. C., Bordin, S., Saad, M. J., & Velloso, L. A. (2009). Saturated fatty acids produce an inflammatory response predominantly through the activation of TLR4 signaling in hypothalamus: Implications for the pathogenesis of obesity. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, *29*(2), 359–370. https://doi.org/10.1523/JNEUROSCI.2760-08.2009

Moheet, A., Mangia, S., & Seaquist, E. (2015). Impact of diabetes on cognitive function and brain structure. *Annals of the New York Academy of Sciences*, *1353*, 60–71. https://doi.org/10.1111/nyas.12807

Morell, P., & Fiszman, S. (2017). Revisiting the role of protein-induced satiation and satiety. *Food Hydrocolloids*, *68*, 199–210. https://doi.org/10.1016/j.foodhyd.2016.08.003

Morris, M. C., Evans, D. A., Tangney, C. C., Bienias, J. L., Schneider, J. A., Wilson, R. S., & Scherr, P. A. (2006). Dietary Copper and High Saturated and trans Fat Intakes Associated With Cognitive Decline. *Archives of Neurology*, *63*(8), 1085–1088. https://doi.org/10.1001/archneur.63.8.1085

Morton, G. J. (2007). Hypothalamic leptin regulation of energy homeostasis and glucose metabolism. *The Journal of Physiology*, *583*(Pt 2), 437–443. https://doi.org/10.1113/jphysiol.2007.135590

Müller, M., Hermes, G. D. A., Emanuel E., C., Holst, J. J., Zoetendal, E. G., Smidt, H., Troost, F., Schaap, F. G., Damink, S. O., Jocken, J. W. E., Lenaerts, K., Masclee, A. A. M., & Blaak, E. E. (2020). Effect of wheat bran derived prebiotic supplementation on gastrointestinal transit, gut microbiota, and metabolic health: A randomized controlled trial in healthy adults with a slow gut transit. *Gut Microbes*, *12*(1), 1704141. https://doi.org/10.1080/19490976.2019.1704141

Mumme, K. D., Conlon, C., von Hurst, P. R., Jones, B., de Seymour, J. V., Stonehouse, W., Heath, A.-L., Coad, J., Haskell-Ramsay, C. F., Mugridge, O., Slade, C., & Beck, K. L. (2022). Associations between dietary patterns and the metabolic syndrome in older adults in New Zealand: The REACH study. *British Journal of Nutrition*, *128*(9), 1806–1816. https://doi.org/10.1017/S0007114521004682

Munteanu, C., & Schwartz, B. (2022). The relationship between nutrition and the immune system. *Frontiers in Nutrition*, *9*. https://www.frontiersin.org/articles/10.3389/fnut.2022.1082500

Murman, D. L. (2015). The Impact of Age on Cognition. *Seminars in Hearing*, *36*(3), 111–121. https://doi.org/10.1055/s-0035-1555115

Ngabirano, L., Samieri, C., Feart, C., Gabelle, A., Artero, S., Duflos, C., Berr, C., & Mura, T. (2019). Intake of Meat, Fish, Fruits, and Vegetables and Long-Term Risk of Dementia and Alzheimer’s Disease. *Journal of Alzheimer’s Disease*, *68*(2), 711–722. https://doi.org/10.3233/JAD-180919

Niedzwiedz, E., & Wadolowska, L. (2008). Accuracy Analysis of the Food Intake Variety Questionnaire (FIVeQ). Reproducibility Assessment among Older People. *Pakistan Journal of Nutrition*, *7*(3), 426–435. https://doi.org/10.3923/pjn.2008.426.435

Noble, E. E., Hsu, T. M., & Kanoski, S. E. (2017). Gut to Brain Dysbiosis: Mechanisms Linking Western Diet Consumption, the Microbiome, and Cognitive Impairment. *Frontiers in Behavioral Neuroscience*, *11*. https://doi.org/10.3389/fnbeh.2017.00009

Noble, E. E., Hsu, T. M., Liang, J., & Kanoski, S. E. (2019). Early life sugar consumption has long-term negative effects on memory function in male rats. *Nutritional Neuroscience*, *22*(4), 273–283. https://doi.org/10.1080/1028415X.2017.1378851

Noble, E. E., & Kanoski, S. E. (2016). Early life exposure to obesogenic diets and learning and memory dysfunction. *Current Opinion in Behavioral Sciences*, *9*, 7–14. https://doi.org/10.1016/j.cobeha.2015.11.014

Noble, E. E., Olson, C. A., Davis, E., Tsan, L., Chen, Y.-W., Schade, R., Liu, C., Suarez, A., Jones, R. B., de La Serre, C., Yang, X., Hsiao, E. Y., & Kanoski, S. E. (2021). Gut microbial taxa elevated by dietary sugar disrupt memory function. *Translational Psychiatry*, *11*(1), Article 1. https://doi.org/10.1038/s41398-021-01309-7

Nurk, E., Drevon, C. A., Refsum, H., Solvoll, K., Vollset, S. E., Nygård, O., Nygaard, H. A., Engedal, K., Tell, G. S., & Smith, A. D. (2007). Cognitive performance among the elderly and dietary fish intake: The Hordaland Health Study. *The American Journal of Clinical Nutrition*, *86*(5), 1470–1478. https://doi.org/10.1093/ajcn/86.5.1470

Nyberg, L., Lövdén, M., Riklund, K., Lindenberger, U., & Bäckman, L. (2012). Memory aging and brain maintenance. *Trends in Cognitive Sciences*, *16*(5), 292–305. https://doi.org/10.1016/j.tics.2012.04.005

O’Donovan, S. M., Crowley, E. K., Brown, J. R.-M., O’Sullivan, O., O’Leary, O. F., Timmons, S., Nolan, Y. M., Clarke, D. J., Hyland, N. P., Joyce, S. A., Sullivan, A. M., & O’Neill, C. (2020). Nigral overexpression of α-synuclein in a rat Parkinson’s disease model indicates alterations in the enteric nervous system and the gut microbiome. *Neurogastroenterology & Motility*, *32*(1), e13726. https://doi.org/10.1111/nmo.13726

Oksanen, J., Blanchet, F. G., Kindt, R., LEGENDRE, P., MINCHIN, P., O’HARA, R., Simpson, G., Solymos, P., STEVENS, M., & Wagner, H. (2012). Vegan: Community ecology package. *The Comprehensive R Archive Network*.

Oldham-Cooper, R. E., Hardman, C. A., Nicoll, C. E., Rogers, P. J., & Brunstrom, J. M. (2011). Playing a computer game during lunch affects fullness, memory for lunch, and later snack intake. *The American Journal of Clinical Nutrition*, *93*(2), 308–313. https://doi.org/10.3945/ajcn.110.004580

Oliveira-Maia, A. J., Roberts, C. D., Simon, S. A., & Nicolelis, M. A. L. (2011). Gustatory and reward brain circuits in the control of food intake. *Advances and Technical Standards in Neurosurgery*, *36*, 31–59. https://doi.org/10.1007/978-3-7091-0179-7_3

O'Mahony, S. M., Clarke, G., Borre, Y. E., Dinan, T. G., & Cryan, J. F. (2015). Serotonin, tryptophan metabolism and the brain-gut-microbiome axis. *Behavioural Brain Research*, *277*, 32–48. https://doi.org/10.1016/j.bbr.2014.07.027

Page, K. C., Jones, E. K., & Anday, E. K. (2014). Maternal and postweaning high-fat diets disturb hippocampal gene expression, learning, and memory function. *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology*, *306*(8), R527–R537. https://doi.org/10.1152/ajpregu.00319.2013

Palta, P., Schneider, A. L. C., Biessels, G. J., Touradji, P., & Hill-Briggs, F. (2014). Magnitude of Cognitive Dysfunction in Adults with Type 2 Diabetes: A Meta-analysis of Six Cognitive Domains and the Most Frequently Reported Neuropsychological Tests Within Domains. *Journal of the International Neuropsychological Society*, *20*(3), 278–291. https://doi.org/10.1017/S1355617713001483

Pammer, L. M., Lamina, C., Schultheiss, U. T., Kotsis, F., Kollerits, B., Stockmann, H., Lipovsek, J., Meiselbach, H., Busch, M., Eckardt, K.-U., Kronenberg, F., & Investigators, for the G. (2021). Association of the metabolic syndrome with mortality and major adverse cardiac events: A large chronic kidney disease cohort. *Journal of Internal Medicine*, *290*(6), 1219–1232. https://doi.org/10.1111/joim.13355

Pasinetti, G. M., & Eberstein, J. A. (2008). METABOLIC SYNDROME AND THE ROLE OF DIETARY LIFESTYLES IN ALZHEIMER'S DISEASE. *Journal of Neurochemistry*, *106*(4), 1503–1514. https://doi.org/10.1111/j.1471-4159.2008.05454.x

Patil, I. (2021). Visualizations with statistical details: The "ggstatsplot" approach. *The Journal of Open Source Software*, *6*, 3167. https://doi.org/10.21105/joss.03167

Penczynski, K. J., Herder, C., Krupp, D., Rienks, J., Egert, S., Wudy, S. A., Roden, M., Remer, T., & Buyken, A. E. (2019). Flavonoid intake from fruit and vegetables during adolescence is prospectively associated with a favourable risk factor profile for type 2 diabetes in early adulthood. *European Journal of Nutrition*, *58*(3), 1159–1172. https://doi.org/10.1007/s00394-018-1631-3

Perez-Pardo, P., Kliest, T., Dodiya, H. B., Broersen, L. M., Garssen, J., Keshavarzian, A., & Kraneveld, A. D. (2017). The gut-brain axis in Parkinson's disease: Possibilities for food-based therapies. *European Journal of Pharmacology*, *817*, 86–95. https://doi.org/10.1016/j.ejphar.2017.05.042

Peters, M., Laeng, B., Latham, K., Jackson, M., Zaiyouna, R., & Richardson, C. (1995). A Redrawn Vandenberg and Kuse Mental Rotations Test—Different Versions and Factors That Affect Performance. *Brain and Cognition*, *28*(1), 39–58. https://doi.org/10.1006/brcg.1995.1032

Petersen, C., Wankhade, U. D., Bharat, D., Wong, K., Mueller, J. E., Chintapalli, S. V., Piccolo, B. D., Jalili, T., Jia, Z., Symons, J. D., Shankar, K., & Anandh Babu, P. V. (2019). Dietary supplementation with strawberry induces marked changes in the composition and functional potential of the gut microbiome in diabetic mice. *The Journal of Nutritional Biochemistry*, *66*, 63–69. https://doi.org/10.1016/j.jnutbio.2019.01.004

Petersson, S. D., & Philippou, E. (2016). Mediterranean Diet, Cognitive Function, and Dementia: A Systematic Review of the Evidence123. *Advances in Nutrition*, *7*(5), 889–904. https://doi.org/10.3945/an.116.012138

Petrovich, G. D. (2011). Learning and the motivation to eat: Forebrain circuitry. *Physiology & Behavior*, *104*(4), 582. https://doi.org/10.1016/j.physbeh.2011.04.059

Piwowarek, K., Lipińska, E., Hać-Szymańczuk, E., Kieliszek, M., & Ścibisz, I. (2018). Propionibacterium spp.-source of propionic acid, vitamin B12, and other metabolites important for the industry. *Applied Microbiology and Biotechnology*, *102*(2), 515–538. https://doi.org/10.1007/s00253-017-8616-7

Plassmann, H., Schelski, D. S., Simon, M., & Koban, L. (2022). How we decide what to eat: Toward an interdisciplinary model of gut–brain interactions. *Wiley Interdisciplinary Reviews. Cognitive Science*, *13*(1), e1562. https://doi.org/10.1002/wcs.1562

Price, M. N., Dehal, P. S., & Arkin, A. P. (2010). FastTree 2 – Approximately Maximum-Likelihood Trees for Large Alignments. *PLOS ONE*, *5*(3), e9490. https://doi.org/10.1371/journal.pone.0009490

Quan, W., Xu, Y., Luo, J., Zeng, M., He, Z., Shen, Q., & Chen, J. (2022). Association of dietary meat consumption habits with neurodegenerative cognitive impairment: An updated systematic review and dose–response meta-analysis of 24 prospective cohort studies. *Food & Function*, *13*(24), 12590–12601. https://doi.org/10.1039/D2FO03168J

Quigley, C., & Müller, M. M. (2014). Feature-Selective Attention in Healthy Old Age: A Selective Decline in Selective Attention? *The Journal of Neuroscience*, *34*(7), 2471–2476. https://doi.org/10.1523/JNEUROSCI.2718-13.2014

Rakhra, V., Galappaththy, S. L., Bulchandani, S., & Cabandugama, P. K. (2020). Obesity and the Western Diet: How We Got Here. *Missouri Medicine*, *117*(6), 536–538.

Reichelt, A. C., Killcross, S., Hambly, L. D., Morris, M. J., & Westbrook, R. F. (2015). Impact of adolescent sucrose access on cognitive control, recognition memory, and parvalbumin immunoreactivity. *Learning & Memory*, *22*(4), 215–224. https://doi.org/10.1101/lm.038000.114

Revelle, W. (2013). psych: Procedures for Psychological, Psychometric, and Personality Research. R Package Version 1.0–95. *Evanston, Illinois*.

Rey-Mermet, A., & Gade, M. (2018). Inhibition in aging: What is preserved? What declines? A meta-analysis. *Psychonomic Bulletin & Review*, *25*(5), 1695–1716. https://doi.org/10.3758/s13423-017-1384-7

Riolo, R., De Rosa, R., Simonetta, I., & Tuttolomondo, A. (2022). Olive Oil in the Mediterranean Diet and Its Biochemical and Molecular Effects on Cardiovascular Health through an Analysis of

Genetics and Epigenetics. *International Journal of Molecular Sciences*, *23*(24), Article 24. https://doi.org/10.3390/ijms232416002

Robeson, M. S., O'Rourke, D. R., Kaehler, B. D., Ziemski, M., Dillon, M. R., Foster, J. T., & Bokulich, N. A. (2020). *RESCRIPt: Reproducible sequence taxonomy reference database management for the masses* (p. 2020.10.05.326504). bioRxiv. https://doi.org/10.1101/2020.10.05.326504

Rodrigues, B., Asamane, E. A., Magalhães, R., Sousa, N., Thompson, J. L., & Santos, N. C. (2020). The association of dietary patterns with cognition through the lens of neuroimaging-a Systematic review. *Ageing Research Reviews*, *63*, 101145. https://doi.org/10.1016/j.arr.2020.101145

Rogers, G. B., Keating, D. J., Young, R. L., Wong, M.-L., Licinio, J., & Wesselingh, S. (2016). From gut dysbiosis to altered brain function and mental illness: Mechanisms and pathways. *Molecular Psychiatry*, *21*(6), 738–748. https://doi.org/10.1038/mp.2016.50

Rold, L. S., Bundgaard-Nielsen, C., Niemann Holm-Jacobsen, J., Glud Ovesen, P., Leutscher, P., Hagstrøm, S., & Sørensen, S. (2022). Characteristics of the gut microbiome in women with gestational diabetes mellitus: A systematic review. *PLoS ONE*, *17*(1), e0262618. https://doi.org/10.1371/journal.pone.0262618

Rolls, E. T. (2021). The orbitofrontal cortex, food reward, body weight and obesity. *Social Cognitive and Affective Neuroscience*, *18*(1), nsab044. https://doi.org/10.1093/scan/nsab044

Rossi, M. A., & Stuber, G. D. (2018). Overlapping Brain Circuits for Homeostatic and Hedonic Feeding. *Cell Metabolism*, *27*(1), 42–56. https://doi.org/10.1016/j.cmet.2017.09.021

Rozin, P., Dow, S., Moscovitch, M., & Rajaram, S. (1998). What Causes Humans to Begin and End a Meal? A Role for Memory for What Has Been Eaten, as Evidenced by a Study of Multiple Meal Eating in Amnesic Patients. *Psychological Science*, *9*(5), 392–396. https://doi.org/10.1111/1467-9280.00073

Salthouse, T. A. (2006). Mental Exercise and Mental Aging: Evaluating the Validity of the “Use It or Lose It” Hypothesis. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science*, *1*(1), 68–87. https://doi.org/10.1111/j.1745-6916.2006.00005.x

Salthouse, T. A. (2009). When does age-related cognitive decline begin? *Neurobiology of Aging*, *30*(4), 507–514. https://doi.org/10.1016/j.neurobiolaging.2008.09.023

Salthouse, T. A. (2010). Selective review of cognitive aging. *Journal of the International Neuropsychological Society*, *16*(5), 754–760. https://doi.org/10.1017/S1355617710000706

Salthouse, T. A. (2011). Neuroanatomical substrates of age-related cognitive decline. *Psychological Bulletin*, *137*(5), 753–784. https://doi.org/10.1037/a0023262

Samieri, C., Grodstein, F., Rosner, B. A., Kang, J. H., Cook, N. R., Manson, J. E., Buring, J. E., Willett, W. C., & Okereke, O. I. (2013). Mediterranean diet and cognitive function in older age: Results from the Women’s Health Study. *Epidemiology (Cambridge, Mass.)*, *24*(4), 490–499. https://doi.org/10.1097/EDE.0b013e318294a065

Sample, C. H., Jones, S., Hargrave, S. L., Jarrard, L. E., & Davidson, T. L. (2016). Western Diet and the Weakening of the Interoceptive Stimulus Control of Appetitive Behavior. *Behavioural Brain Research*, *312*, 219–230. https://doi.org/10.1016/j.bbr.2016.06.020

Sarkar, A., Harty, S., Lehto, S. M., Moeller, A. H., Dinan, T. G., Dunbar, R. I. M., Cryan, J. F., & Burnet, P. W. J. (2018). The Microbiome in Psychology and Cognitive Neuroscience. *Trends in Cognitive Sciences*, *22*(7), 611–636. https://doi.org/10.1016/j.tics.2018.04.006

Sarkar, A., Lehto, S. M., Harty, S., Dinan, T. G., Cryan, J. F., & Burnet, P. W. J. (2016). Psychobiotics and the Manipulation of Bacteria–Gut–Brain Signals. *Trends in Neurosciences*, *39*(11), 763–781. https://doi.org/10.1016/j.tins.2016.09.002

Sato, W. (2020). Association Between Dieting Failure and Unconscious Hedonic Responses to Food. *Frontiers in Psychology*, *11*, 2089. https://doi.org/10.3389/fpsyg.2020.02089

Scarmeas, N., Anastasiou, C. A., & Yannakoulia, M. (2018). Nutrition and prevention of cognitive impairment. *The Lancet Neurology*, *17*(11), 1006–1015. https://doi.org/10.1016/S1474-4422(18)30338-7

Schmitt, J. a. J., Wingen, M., Ramaekers, J. G., Evers, E. a. T., & Riedel, W. J. (2006). Serotonin and human cognitive performance. *Current Pharmaceutical Design*, *12*(20), 2473–2486. https://doi.org/10.2174/138161206777698909

Scholey, A., & Owen, L. (2013). Effects of chocolate on cognitive function and mood: A systematic review. *Nutrition Reviews*, *71*(10), 665–681. https://doi.org/10.1111/nure.12065

Seel, W., Reiners, S., Kipp, K., Simon, M.-C., & Dawczynski, C. (2023). Role of Dietary Fiber and Energy Intake on Gut Microbiome in Vegans, Vegetarians, and Flexitarians in Comparison to Omnivores—Insights from the Nutritional Evaluation (NuEva) Study. *Nutrients*, *15*(8), Article 8. https://doi.org/10.3390/nu15081914

Skevington, S. M., Lotfy, M., & O'Connell, K. A. (2004). The World Health Organization's WHOQOL-BREF quality of life assessment: Psychometric properties and results of the international field trial. A Report from the WHOQOL Group. *Quality of Life Research*, *13*(2), 299–310. https://doi.org/10.1023/B:QURE.0000018486.91360.00

Small, D. M., & DiFeliceantonio, A. G. (2019). Processed foods and food reward. *Science*, *363*(6425), 346–347. https://doi.org/10.1126/science.aav0556

Smith, M. A., Riby, L. M., Eekelen, J. A. M. van, & Foster, J. K. (2011). Glucose enhancement of human memory: A comprehensive research review of the glucose memory facilitation effect. *Neuroscience and Biobehavioral Reviews*, *35*(3), 770–783. https://doi.org/10.1016/j.neubiorev.2010.09.008

Smith, P. M., & Ferguson, A. V. (2008). Neurophysiology of hunger and satiety. *Developmental Disabilities Research Reviews*, *14*(2), 96–104. https://doi.org/10.1002/ddrr.13

Smith, R. P., Easson, C., Lyle, S. M., Kapoor, R., Donnelly, C. P., Davidson, E. J., Parikh, E., Lopez, J. V., & Tartar, J. L. (2019). Gut microbiome diversity is associated with sleep physiology in humans. *PLOS ONE*, *14*(10), e0222394. https://doi.org/10.1371/journal.pone.0222394

Smyth, A., Dehghan, M., O'Donnell, M., Anderson, C., Teo, K., Gao, P., Sleight, P., Dagenais, G., Probstfield, J. L., Mente, A., & Yusuf, S. (2015). Healthy eating and reduced risk of cognitive decline: A cohort from 40 countries. *Neurology*, *84*(22), 2258–2265. https://doi.org/10.1212/WNL.0000000000001638

Sobesky, J. L., D’Angelo, H. M., Weber, M. D., Anderson, N. D., Frank, M. G., Watkins, L. R., Maier, S. F., & Barrientos, R. M. (2016). Glucocorticoids Mediate Short-Term High-Fat Diet Induction of Neuroinflammatory Priming, the NLRP3 Inflammasome, and the Danger Signal HMGB1. *ENeuro*, *3*(4), ENEURO.0113-16.2016. https://doi.org/10.1523/ENEURO.0113-16.2016

Sonali, S., Ray, B., Ahmed Tousif, H., Rathipriya, A. G., Sunanda, T., Mahalakshmi, A. M., Rungratanawanich, W., Essa, M. M., Qoronfleh, M. W., Chidambaram, S. B., & Song, B.-J. (2022). Mechanistic Insights into the Link between Gut Dysbiosis and Major Depression: An Extensive Review. *Cells*, *11*(8), Article 8. https://doi.org/10.3390/cells11081362

Spencer, S. J., Korosi, A., Layé, S., Shukitt-Hale, B., & Barrientos, R. M. (2017). Food for thought: How nutrition impacts cognition and emotion. *Npj Science of Food*, *1*(1), 7. https://doi.org/10.1038/s41538-017-0008-y

Spielberger, C. D., & Sydeman, S. J. (1994). State-Trait Anxiety Inventory and State-Trait Anger Expression Inventory. In *The use of psychological testing for treatment planning and outcome assessment* (pp. 292–321). Lawrence Erlbaum Associates, Inc.

Staiano, A. E., Martin, C. K., Champagne, C. M., Rood, J. C., & Katzmarzyk, P. T. (2018). Sedentary time, physical activity, and adiposity in a longitudinal cohort of nonobese young adults. *The American Journal of Clinical Nutrition*, *108*(5), 946–952. https://doi.org/10.1093/ajcn/nqy191

Steinert, R. E., Feinle-Bisset, C., Asarian, L., Horowitz, M., Beglinger, C., & Geary, N. (2017). Ghrelin, CCK, GLP-1, and PYY(3–36): Secretory Controls and Physiological Roles in Eating and Glycemia in Health, Obesity, and After RYGB. *Physiological Reviews*, *97*(1), 411–463. https://doi.org/10.1152/physrev.00031.2014

Sternberg, S. (1966). High-Speed Scanning in Human Memory. *Science*, *153*(3736), 652–654. https://doi.org/10.1126/science.153.3736.652

Stevenson, R. J., Francis, H. M., Attuquayefio, T., Gupta, D., Yeomans, M. R., Oaten, M. J., & Davidson, T. (2020). Hippocampal-dependent appetitive control is impaired by experimental exposure to a Western-style diet. *Royal Society Open Science*, *7*(2), 191338. https://doi.org/10.1098/rsos.191338

Stubbs, R. J. (1999). Peripheral signals affecting food intake. *Nutrition*, *15*(7), 614–625. https://doi.org/10.1016/S0899-9007(99)00098-2

Suarez, A. N., Noble, E. E., & Kanoski, S. E. (2019). Regulation of Memory Function by Feeding-Relevant Biological Systems: Following the Breadcrumbs to the Hippocampus. *Frontiers in Molecular Neuroscience*, *12*, 101. https://doi.org/10.3389/fnmol.2019.00101

Sudo, N., Chida, Y., Aiba, Y., Sonoda, J., Oyama, N., Yu, X.-N., Kubo, C., & Koga, Y. (2004). Postnatal microbial colonization programs the hypothalamic-pituitary-adrenal system for stress response in mice: Commensal microbiota and stress response. *The Journal of Physiology*, *558*(1), 263–275. https://doi.org/10.1113/jphysiol.2004.063388

Suthahar, N., Wang, K., Zwartkruis, V. W., Bakker, S. J. L., Inzucchi, S. E., Meems, L. M. G., Eijgenraam, T. R., Ahmadizar, F., Sijbrands, E. G., Gansevoort, R. T., Kieneker, L. M., Veldhuisen, D. J. van, Kavousi, M., & Boer, R. A. de. (2023). Associations of relative fat mass, a new index of adiposity, with type-2 diabetes in the general population. *European Journal of Internal Medicine*, *109*, 73–78. https://doi.org/10.1016/j.ejim.2022.12.024

Talebi, S., Asoudeh, F., Naeini, F., Sadeghi, E., Travica, N., & Mohammadi, H. (2023). Association between animal protein sources and risk of neurodegenerative diseases: A systematic review and dose-response meta-analysis. *Nutrition Reviews*, nuac114. https://doi.org/10.1093/nutrit/nuac114

Tillisch, K., Labus, J., Kilpatrick, L., Jiang, Z., Stains, J., Ebrat, B., Guyonnet, D., Legrain-Raspaud, S., Trotin, B., Naliboff, B., & Mayer, E. A. (2013). Consumption of fermented milk product with probiotic modulates brain activity. *Gastroenterology*, *144*(7), 1394–1401, 1401.e1-4. https://doi.org/10.1053/j.gastro.2013.02.043

Tozuka, Y., Kumon, M., Wada, E., Onodera, M., Mochizuki, H., & Wada, K. (2010). Maternal obesity impairs hippocampal BDNF production and spatial learning performance in young mouse offspring. *Neurochemistry International*, *57*(3), 235–247. https://doi.org/10.1016/j.neuint.2010.05.015

Tulsky, D. S., Chiaravalloti, N. D., Palmer, B. W., & Chelune, G. J. (2003). The Wechsler Memory Scale, Third Edition: A new perspective. In *Clinical interpretation of the WAIS-III and WMS-III* (pp. 93–139). Academic Press. https://doi.org/10.1016/B978-012703570-3/50007-9

Turnbaugh, P. J., Ley, R. E., Mahowald, M. A., Magrini, V., Mardis, E. R., & Gordon, J. I. (2006). An obesity-associated gut microbiome with increased capacity for energy harvest. *Nature*, *444*(7122), 1027–1031. https://doi.org/10.1038/nature05414

Turnbaugh, P. J., Ridaura, V. K., Faith, J. J., Rey, F. E., Knight, R., & Gordon, J. I. (2009). The effect of diet on the human gut microbiome: A metagenomic analysis in humanized gnotobiotic mice. *Science Translational Medicine*, *1*(6), 6ra14. https://doi.org/10.1126/scitranslmed.3000322

van den Brink, A. C., Brouwer-Brolsma, E. M., Berendsen, A. A. M., & van de Rest, O. (2019). The Mediterranean, Dietary Approaches to Stop Hypertension (DASH), and Mediterranean-DASH Intervention for Neurodegenerative Delay (MIND) Diets Are Associated with Less Cognitive Decline and a Lower Risk of Alzheimer's Disease—A Review. *Advances in Nutrition*, *10*(6), 1040–1065. https://doi.org/10.1093/advances/nmz054

Wachsmuth, H. R., Weninger, S. N., & Duca, F. A. (2022). Role of the gut–brain axis in energy and glucose metabolism. *Experimental & Molecular Medicine*, *54*(4), Article 4. https://doi.org/10.1038/s12276-021-00677-w

Wadolowska, L. (2005). Walidacja kwestionariusza czestotliwosci spozycia zywnosci—FFQ. Ocena powtarzalnosci. *Bromatologia i Chemia Toksykologiczna*, *38*(1), 27–33.

Wallace, T. C., & Giusti, M. M. (2015). Anthocyanins1. *Advances in Nutrition*, *6*(5), 620–622. https://doi.org/10.3945/an.115.009233

Weinstein, G., Vered, S., Ivancovsky-Wajcman, D., Ravona-Springer, R., Heymann, A., Zelber-Sagi, S., Shahar, D. R., & Beeri, M. S. (2023). Consumption of Ultra-Processed Food and Cognitive Decline among Older Adults With Type-2 Diabetes. *The Journals of Gerontology. Series A, Biological Sciences and Medical Sciences*, *78*(1), 134–142. https://doi.org/10.1093/gerona/glac070

Weisberg, S., & Fox, J. (2011). *An R Companion to Applied Regression*. Thousand Oaks: Sage.

Weyh, C., Krüger, K., Peeling, P., & Castell, L. (2022). The Role of Minerals in the Optimal Functioning of the Immune System. *Nutrients*, *14*(3), 644. https://doi.org/10.3390/nu14030644

White, C. L., Pistell, P. J., Purpera, M. N., Gupta, S., Fernandez-Kim, S.-O., Hise, T. L., Keller, J. N., Ingram, D. K., Morrison, C. D., & Bruce-Keller, A. J. (2009). Effects of high fat diet on Morris maze performance, oxidative stress, and inflammation in rats: Contributions of maternal diet. *Neurobiology of Disease*, *35*(1), 3–13. https://doi.org/10.1016/j.nbd.2009.04.002

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., … Yutani, H. (2019). Welcome to the Tidyverse. *Journal of Open Source Software*, *4*(43), 1686. https://doi.org/10.21105/joss.01686

Williamson, C., Foster, R., Stanner, S., & Buttriss, J. (2005). Red meat in the diet. *Nutrition Bulletin*, *30*. https://doi.org/10.1111/j.1467-3010.2005.00525.x

Willis, A. D. (2019). Rarefaction, Alpha Diversity, and Statistics. *Frontiers in Microbiology*, *10*. https://www.frontiersin.org/articles/10.3389/fmicb.2019.02407

Wingrove, K., Lawrence, M. A., & McNaughton, S. A. (2022). A Systematic Review of the Methods Used to Assess and Report Dietary Patterns. *Frontiers in Nutrition*, *9*, 892351. https://doi.org/10.3389/fnut.2022.892351

Woods, S. C. (2004). Gastrointestinal Satiety Signals I. An overview of gastrointestinal signals that influence food intake. *American Journal of Physiology-Gastrointestinal and Liver Physiology*, *286*(1), G7–G13. https://doi.org/10.1152/ajpgi.00448.2003

Woods, S. P., Delis, D. C., Scott, J. C., Kramer, J. H., & Holdnack, J. A. (2006). The California Verbal Learning Test--second edition: Test-retest reliability, practice effects, and reliable change indices for the standard and alternate forms. *Archives of Clinical Neuropsychology*, *21*(5), 413–420. https://doi.org/10.1016/j.acn.2006.06.002

Woolcott, O. O., & Bergman, R. N. (2018). Relative fat mass (RFM) as a new estimator of whole-body fat percentage ─ A cross-sectional study in American adult individuals. *Scientific Reports*, *8*(1), Article 1. https://doi.org/10.1038/s41598-018-29362-1

Wu, G. D., Compher, C., Chen, E. Z., Smith, S. A., Shah, R. D., Bittinger, K., Chehoud, C., Albenberg, L. G., Nessel, L., Gilroy, E., Star, J., Weljie, A. M., Flint, H. J., Metz, D. C., Bennett, M. J., Li, H., Bushman, F. D., & Lewis, J. D. (2016). Comparative metabolomics in vegans and omnivores reveal constraints on diet-dependent gut microbiota metabolite production. *Gut*, *65*(1), 63–72. https://doi.org/10.1136/gutjnl-2014-308209

Yates, K. F., Sweat, V., Yau, P. L., Turchiano, M. M., & Convit, A. (2012). Impact of Metabolic Syndrome on Cognition and Brain: A Selected Review of the Literature. *Arteriosclerosis, Thrombosis, and Vascular Biology*, *32*(9), 2060–2067. https://doi.org/10.1161/ATVBAHA.112.252759

Yeh, T.-S., Blacker, D., & Ascherio, A. (2021). To meat or not to meat? Processed meat and risk of dementia. *The American Journal of Clinical Nutrition*, *114*(1), 7–8. https://doi.org/10.1093/ajcn/nqab139

Ylilauri, M. P. T., Hantunen, S., Lönnroos, E., Salonen, J. T., Tuomainen, T.-P., & Virtanen, J. K. (2022). Associations of dairy, meat, and fish intakes with risk of incident dementia and with cognitive performance: The Kuopio Ischaemic Heart Disease Risk Factor Study (KIHD). *European Journal of Nutrition*, *61*(5), 2531–2542. https://doi.org/10.1007/s00394-022-02834-x

Zanchi, D., Depoorter, A., Egloff, L., Haller, S., Mählmann, L., Lang, U. E., Drewe, J., Beglinger, C., Schmidt, A., & Borgwardt, S. (2017). The impact of gut hormones on the neural circuit of appetite and satiety: A systematic review. *Neuroscience & Biobehavioral Reviews*, *80*, 457–475. https://doi.org/10.1016/j.neubiorev.2017.06.013

Zhang, H., Greenwood, D. C., Risch, H. A., Bunce, D., Hardie, L. J., & Cade, J. E. (2021). Meat consumption and risk of incident dementia: Cohort study of 493,888 UK Biobank participants. *The American Journal of Clinical Nutrition*, *114*(1), 175–184. https://doi.org/10.1093/ajcn/nqab028

Zhang, H., Hardie, L., Bawajeeh, A. O., & Cade, J. (2020). Meat Consumption, Cognitive Function and Disorders: A Systematic Review with Narrative Synthesis and Meta-Analysis. *Nutrients*, *12*(5), 1528. https://doi.org/10.3390/nu12051528

Zhang, P., Huang, P., Du, J., He, Y., Liu, J., He, G., Cui, S., Zhang, W., Li, G., & Chen, S. (2022). Specific gut microbiota alterations in essential tremor and its difference from Parkinson's disease. *Npj Parkinson's Disease*, *8*(1), Article 1. https://doi.org/10.1038/s41531-022-00359-y

Zhao, E., Zhang, W., Geng, B., You, B., Wang, W., & Li, X. (2021). Intestinal dysbacteriosis leads to kidney stone disease. *Molecular Medicine Reports*, *23*(3), 1–1. https://doi.org/10.3892/mmr.2020.11819

Zheng, H., Lenard, N. R., Shin, A. C., & Berthoud, H.-R. (2009). Appetite control and energy balance regulation in the modern world: Reward-driven brain overrides repletion signals. *International Journal of Obesity*, *33*(2), Article 2. https://doi.org/10.1038/ijo.2009.65

Zheng, S., Zhu, Y., Wu, W., Zhang, Q., Wang, Y., Wang, Z., & Yang, F. (2021). A correlation study of intestinal microflora and first-episode depression in Chinese patients and healthy volunteers. *Brain and Behavior*, *11*(8), e02036. https://doi.org/10.1002/brb3.2036

Zupo, R., Griseta, C., Battista, P., Donghia, R., Guerra, V., Castellana, F., Lampignano, L., Bortone, I., Lozupone, M., Giannelli, G., De Pergola, G., Boeing, H., Sardone, R., & Panza, F. (2022). Role of plant-based diet in late-life cognitive decline: Results from the Salus in Apulia Study.

Nutritional Neuroscience, *25*(6), 1300–1309.

https://doi.org/10.1080/1028415X.2020.1853416