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EYE-TRACKING THE VISUAL PREFERENCES OF THE MORBIDLY OBESE IN RELATION TO CALORIC DENSITY

Master Thesis

submitted by

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Abstract

This work investigates the relationship between a person's Body Mass Index (BMI) and their gaze patterns when viewing paired images of foods (marked as "Areas of Interest" or "AOIs") of similar visual appearance but significantly different caloric density. With ample scientific evidence for a statistical correlation between obesity and subconscious mental and neurophysiological processes that promote a higher level of attention to food and thus greater food intake, we expected people with higher BMIs to have their point of gaze subconsciously drawn towards foods of higher caloric density.

We were, however, unable to ascertain consistently significant relationships between a person's BMI and a visual preference for high-calorie food. Instead, we found gaze patterns to be highly susceptible to participant-intrinsic and test-setup-related factors. Specifically, there exists a clear bias (as evidenced by a significantly lower Time to First Fixation) towards the left side of the screen when starting to examine a new picture, unless the AOI on the right side is situated directly adjacent to the starting point. The size and complexity of the AOI are also highly influential factors – a small cookie was shown to elicit a significantly lower total Fixation Length and Fixation Count than the larger pumpkinseed roll next to it, while an AOI composed of a whole tomato and several sliced ones attracted significantly more attention than a similar-sized AOI composed solely of nearly-identical looking slices of sausage.

There are, however, also indicators that a higher BMI is generally negatively correlated with the number of fixations and total fixation length for objects on the left side of the screen, regardless of their caloric content, although we were not able to statistically discern whether this effect was causally related to the BMI itself or the higher average age of our high-BMI participant group.

Also of interest was that the AOI "cheeseburger", chosen specifically for its plainly visible fat content, produced longer "First Fixation Durations" in overweight participants, suggesting a greater cognitive/emotional impact in these subjects. Interestingly, when questioned verbally after the test, many participants reported being drawn to the burger because they found it disgusting rather than appetizing.

While we settled on a simple linear model as the basis for our regression analysis, a comparison of alternative models in Statgraphics showed that it only rarely produced the highest R^2-values – to our surprise, "exotic" models such as "Reciprocal Y-Squared X" or "Squared Y-Reciprocal X" repeatedly yielded better results.

Zusammenfassung

Diese Arbeit untersucht den Zusammenhang zwischen dem Body Mass Index (BMI) einer Person und ihrem Blickverhalten beim Betrachten von paarweise abgebildeten Nahrungsmitteln (definiert als „Areas of Interest“ oder „AOIs“) mit ähnlichem optischen Erscheinungsbild, aber stark unterschiedlicher kalorischer Dichte. Aufgrund zahlreicher Hinweise auf eine Korrelation zwischen Adipositas und unterbewussten geistigen und neurophysiologischen Effekten, welche eine erhöhte Aufmerksamkeit für nahrungsmittelassoziierte Reize und damit eine erhöhte Nahrungsaufnahme fördern, erwarteten wir, dass der Blick von Testpersonen mit höheren Body Mass Indices unbewusst zu Nahrungsmitteln höherer kalorischer Dichte hingezogen würde.

Tatsächlich waren wir nicht in der Lage, konsistentsignifikante statistische Trends nachzuweisen, die auf einen Zusammenhang zwischen dem BMI einer Person und einer visuellen Präferenz für hochkalorische Nahrungsmittel hindeuten würden. Stattdessen erwiesen sich die Blickmuster der Versuchspersonen in hohem Maße anfällig für personenintrinsische und versuchsaufbaubedingte Faktoren. Besonders auffällig war hier eine deutliche Tendenz der Versuchspersonen, beim Betrachten eines neuen Bilds zunächst das Objekt in der linken Bildhälfte zu fixieren (ungeachtet dessen kalorischer Dichte), außer wenn sich jenes auf der rechten Seite wesentlich näher am anfänglichen Blickpunkt befand. Die Größe und visuelle Komplexität der AOIs waren ebenfalls als Einflussfaktoren erkennbar – während ein relativ kleiner Keks eine signifikant niedrigere Fixationszahl und –dauer erreichte als das danebenplatzierte relativ große Kürbiskernlaibchen, zog ein aus geschnittenen und einer ganzen Tomate zusammengesetztes AOI wesentlich mehr Aufmerksamkeit auf sich als ein lediglich aus optisch ähnlichen Wurstscheiben bestehendes AOI von etwa gleicher Größe.

Es fanden sich allerdings Hinweise, dass ein höherer BMI mit einer geringeren Gesamtfixationsanzahl und –dauer für Objekte auf der linken Seite des Bildschirms korreliert, auch wenn sich statistisch nicht eindeutig feststellen ließ, ob dieser Effekt letztlich eine Folge des Body Mass Index oder des höheren Durchschnittsalters der Versuchspersonen war.

Ebenfalls auffällig war eine positiv mit dem BMI korrelierte Dauer der ersten Fixation auf den gezielt „fettig“ dargestellten Cheeseburger – ein Indiz für eine stärkere kognitive/emotionale Reaktion bei übergewichtigen Versuchspersonen (interessanterweise gaben viele Versuchspersonen im Anschluss an den Test an, dass der Burger deshalb ihre Aufmerksamkeit erregt habe, weil sie ihn als besonders unappetitlich empfanden).

Während wir uns im voraus auf das einfache lineare Modell für unsere Regressionsanalyse festgelegt hatten, zeigte sich beim Vergleich verschiedener alternativer Modelle in Statgraphics, dass dieses nur in Ausnahmefällen die höchsten R^2-Werte ergab – zu unserer Überraschung erwiesen sich hier oft „exotische“ Modelle wie „Reciprocal Y-Squared X“ oder „Squared Y-Reciprocal X“ als ergiebiger.

Acknowledgements

Fig. 1: La Vue [1]

Fig. 2: À mon seul désir [2]

"À Mon Seul Désir" ("To my only desire") – from "La dame à la licorne" ("The Lady and the Unicorn), a series of tapestries crafted in 15th century France. Out of the six tapestries, five represent the classic five senses – taste, hearing, smell, touch and sight, while the sixth bears the inscription *"to my only desire"*. In a sense, the latter two masterpieces sum up the essence of eye tracking – from knowing what a person's gaze is attracted to, we hope to extrapolate their innermost desires, even if they might not be consciously aware of them.

I dedicate this work to my parents Gerald and Gabriele Jöchl and my brother Felix, without whose patience and unwavering support this work would not have been possible, as well as my friends and the rest of my extended family (especially Sepp Weidinger – I so wish I could carry on your genes).

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I would also like to thank all the participants in this study, especially those currently suffering from obesity, whom I wish the best of luck in shaking what some might rightfully call an “addiction” to food. In his novel “Cryptonomicon” [3], the author Neal Stephenson voices his objection to the term “addict”, instead proposing the word *“seeky”* (derived from the German word “süchtig”[1] [4]), i.e. having an *inclination to seek* out the substance of abuse, even when not actively *seeking* it at the present moment. As such, *“seeky”* is an adjective that modifies the person, while “addict” is a noun that obliterates it.

Following this train of thought, any comprehensive attempt at combating obesity needs to approach the sufferer both on a physiological as well as a deep, personal level. Therefore, my gratitude also goes out to the hard-working staff at the Psychosomatisches Zentrum Waldviertel and the Therapiezentrum Buchenberg, not only for their cooperation, but also their dedication to the well-being of their patients.

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[1] Note: Stephenson’s etymology here is faulty – the word “süchtig” is not related to the German “suchen” (to seek), instead being derived from “siechen” (to be sick)

1 Introduction

1.1 Eye Tracking in the Morbidly Obese

According to the incentive sensitization model, the dysregulated eating behaviours that are often the cause of obesity or various eating disorders may be understood as a form of addiction: The activity of the dopaminergic reward system in anticipation of and in response to consuming the “substance of abuse” (i.e. food) causes a sensitization toward reward-related cues, increasing their salience (making them more “attention-grabbing”). The person is thus more likely to notice these cues, increasing the likelihood of experiencing feelings of “craving” and “wanting”, which, in turn, increases overall food intake and promotes further priming of the brain toward food intake.

In a study by Rothemund et al [5], brain imaging using fMRI (functional magnetic resonance imaging) was used to demonstrate that in obese subjects, visual stimulation with food images alone was sufficient to activate the dorsal striatum, an area of the brain involved in reward anticipation and habit learning; furthermore, the level of activation was proportional to the test subjects’ body mass indices. Images of high-calorie foods were also shown to elicit BMI-dependent activations in regions associated with taste information processing (the anterior insula and the lateral orbitofrontal cortex), motivation (orbitofrontal cortex) as well as emotion and memory (posterior cingulate). Interestingly, the activation of the dorsal striatum was shown to be independent of the obese person’s actual physiological level of satiety. The regions of the reward system involved in an obese person’s reaction to food stimuli were also the ones previously shown to have a lower D2 receptor availability similar to what is seen in methamphetamine addicts [6]. The fMRI data also revealed a discrepancy between how the test subjects rated the palatability of the displayed food in a questionnaire and the level of actual emotional response in the brain – low-calorie foods received higher ratings. A similar discrepancy was found in alcoholics exposed to alcohol-related stimuli [7], suggesting that verbal reports are not a reliable measure of actual liking/craving if the test subject is trying to project a more favorable image or is in denial about his or her own state of mind.

The subconscious effects of these process have been demonstrated in a number of tests for the detection of attention biases, such as the dot-probe task, the Stroop task [8] and more recently eye tracking. A study by Nijs et al. [9] explored different methods for comparing differences in attention to food images versus neutral ones. In an eye tracking experiment, both obese and normal-weight women showed a direction bias (which images were preferentially fixated on first) and a duration bias (which images were fixated on the longest) for food images, although there were no statistical differences between the two groups. The P300 ERP (a peak in an EEG reading appearing approximately 300 ms after presentation of a stimulus), a strong indicator of conscious attention allocation, also revealed a bias towards food images in both groups. Interestingly, this bias is greater in hungry normal-weight subjects than in satiated ones, while the opposite seems to be the case in overweight persons – possibly due to a conscious mental effort by the overweight person to shift attention away from the food cue in order to prevent disinhibited food intake. Piech et al. [10] used an Emotional Blink of Attention (EBA) paradigm to demonstrate that a state of hunger significantly increases the attention-capturing effects of food cues (hungry participants were much less likely to identify a target in a sequence of images if it was preceded by a food-related stimulus).

The non-invasive nature of modern eye tracking devices and the low degree of activity required from the participant generally lend themselves well towards experimental setups where the participant is not fully aware of the actual purpose of the experiment, thus allowing insights into their “natural” gaze patterns. Eye tracking as a psychological research tool is part of a growing trend towards “implicit measures”, described by De Houwer as *“measurement outcomes that reflect the to-be-measured construct by virtue of processes that are uncontrolled, unintentional, goal-independent, purely-stimulus-driven, autonomous, unconscious, efficient, or fast”* [11]. While such methods tend to be less susceptible to manipulation than classic “explicit” measurements, they are nonetheless not immune to it, especially when the participants are aware of the purpose of the experiment and have a general understanding of the mechanisms by which the result is produced[12]. In our case, when recruiting participants with specific eating disorders, the person is likely to assume that the experiment is somehow related to his or her condition, and may attempt to consciously influence their gaze patterns in such a way as to produce a more “favorable” result (i.e. averting their gaze from food-related cues). Blatantly obvious attempts at obfuscation may additionally serve to aggravate the patient and deter him from participating altogether. The most common solution for this is the creation of a “plausible” bogus task. A previous experiment by this department [13] (comparing the visual preference between an image of a “healthy” food next to an “unhealthy” one) utilized a memory recall test as the bogus scenario; while certainly fulfilling the requirement of plausibility, it also introduces several potential risks of interference: Because it presents a situation in which the participants feel they can “win” or “lose”, they are likely to try and influence their gaze patterns in such a way as to increase memory retention; furthermore, the situation is likely to create undue stress, particularly in psychologically insecure participants (a fear of being judged “fat AND stupid”). Barring ethical considerations, stress is also known to increase both perceived hunger and attention bias to high-calorie snack foods, and as such should be avoided in the test setup [14-15]. We thus decided to simply reveal as little information as possible and necessary to the participants, claiming to be validating the device rather than “testing” the person.

Naturally, all participants were informed about the true nature of the experiment afterwards, and asked to give consent to us using the data gained under this “false pretense”.

1.2 Motivation

The author could name several inspirations for this paper – personal experiences with sufferers of obesity and anorexia, and a fascination with neurobiology (especially the paradoxical nature of the dopaminergic system) and the chance to work with technology that would have been considered science fiction not too long ago.

Perhaps the greatest motivation, however, was the hope of contributing to the understanding of what may become one of the deadliest epidemics of the 21^{st} century – obesity. Modern non-intrusive eye trackers like the Tobii® system allow for unique insights into our subconscious thought processes, reminding us that the eye is, after all, an outgrowth of the brain.

2 Eye Tracking – an Overview

The term „eye tracking“ refers to experimental techniques designed to measure and visualize the movement of the test subject’s point of gaze and/or the movement of the eye relative to the head. As eye movements are greatly influenced by instinctive or otherwise subconscious processes, it can be used to gain information that the test subject may not be consciously aware of, or is unwilling or unable to communicate (also allowing for insights into the mental processes of test subjects not capable of higher forms of communication, such as animals, infants, or the severely mentally infirm). As such, it has become an invaluable research tool for a wide range of applications in fields like ophthalmology [16], developmental psychology [17], neuroscience [18], marketing research [19] and usability-oriented design [20-21].

With the exception of ophthalmology and related physiological tests, the reliability of an eye tracking paradigm is very much influenced by how “natural” the test is set up. Intrusive technical equipment (like mobile systems requiring the user to wear uncomfortable camera headgear, or stationary devices that require an uncomfortable or unnaturally “stiff” sitting position) can negatively affect the outcome of the experiment; furthermore, the simple feeling of “being watched” may prompt the test subject to consciously direct his gaze away from images that he feels may negatively affect the watcher’s opinion of him (e.g. deliberately avoiding “embarrassing” sexual cues) [20].

Modern commercial eye tracking systems – like the Tobii® device used in this paper - are largely based on the cornea reflex method, in which a (usually infra-red) light source is reflected from the cornea (the so-called “first Purkinje image”) and automatically translated into tracking data using complex algorithms. Other optical methods allow for greater resolution, but are also more intrusive and complex to set up – for example requiring extensive calibration and only allowing for minimal head movements (such as ophthalmologically used “dual Purkinje” eye trackers that require the user to affix their head position through the use of a “bite bar”) or requiring the use of specialized reflective contact lenses; by comparison, a Tobii® eye tracker can be calibrated within seconds. However, in applications requiring maximum precision (such as ophthalmological research or eye surgery), six-dimensional eye tracking capability (i.e. the ability to track both the translational as well as the rotational movements of the eyeball in three dimensions) [22] or frame rates of several hundred hertz may be advantageous or even necessary, making them out of reach of current-generation remote eye trackers.

Camera-based systems can further be divided into head-mounted and stationary (“remote”) systems, the former affording the obvious advantage of greater mobility, but requiring the user to wear potentially intrusive headgear. Furthermore, these headsets can be fitted with additional sensors (e.g. an accelerometer to track head movements), albeit at the cost of additional weight and bulk (although advances in battery technology, optics and electronics have done much to mitigate these issues) [23]. Another advantage of head-mounted systems is the relatively constant distance between the device and the user's eye, thus allowing for very accurate measurements of pupil size [24].

In general, it can be said that with camera-based systems, greater measurement precision always comes at a price (and not only a significant monetary one) – one either has to sacrifice freedom of head movements (in stationary devices) or introduce more complex and heavier headgear. In case of the Tobii® T60 (or similar competing systems such as the SMI RED series [25]), the ability to detect microsaccades (which would necessitate ultra-high frame rates) or similar phenomena is sacrificed in favor of providing a natural, user- and participant-friendly experimental setup, the latter being much more relevant for experiments such as this. However, the next generation of eye trackers (such as the Tobii® TX300 [26] that is expected to hit the market in early 2011) may be able to finally integrate ophthalmology-level precision with the comfort of their predecessors.

Other noteworthy eye tracking techniques involve the use of search coils (coils embedded in a contact lens generate an electric current as they move through an electrical field generated by magnets positioned around the eye) or electrooculograms (electrodes placed around the eye register the electrical potential of the retina). While less precise than other methods, electrooculographic electrodes do not interfere with the user's daily activities, and can be used to track eye movements even when the subject's eyes are closed (e.g. when asleep) [27].

2.1 Tobii® T60 Eye Tracker

The Tobii® T60 Eye Tracker is an optical (near-infrared) eye tracking device utilizing an improved Pupil Centre Corneal Reflection (PCCR) principle. Its dual "bright pupil" (the illuminator is placed near the optical axis of the imaging device, causing the pupil to appear brighter than the iris, similar to the red-eye effect commonly encountered in photography) and "dark pupil" (the illuminator is placed away from the optical axis, the pupil thus appears darker than the iris) capabilities allow for use under a wider range of environmental conditions (changes in pupil size due to environmental lighting conditions can be problematic under the "bright pupil" method) and participants ("bright pupil" usually produces better results in people of European descent, while "dark pupil" works better for Asians [28]; the system automatically determines the optimal method during calibration). By identifying the relative positions of the pupil and the "glint" reflected off the cornea and comparing it to an internal physiological 3D model of the human eye (encompassing data on things like shape, reflection or refraction properties), gaze data can be computed with fairly high precision (at a normal distance from the eye tracking device, the point of gaze on the screen can be determined within less than a centimeter's accuracy). The sensor unit itself consists of two infrared cameras; this "stereo data processing" results in higher precision as well as a greater robustness in regard to changes in head position (eye movements can be reliably tracked at a distance of 50 to 80 cm, with optimum performance achieved at a distance of 70 cm).

The system is also capable of calculating the size of the pupils; variations in pupil size may, for example, provide clues on the emotional impact of an image [29]. While it is generally less suitable for measuring absolute pupil sizes (since the user is free to move his or her head, pupil size has to be calculated in relation to distance from the device, introducing an additional margin of error), fluctuations in size of the individual pupils can be measured with a fairly high degree of precision – a study by Klingner [30] found that a Tobii® 1750 Eye Tracker can determine mean binocular pupil diameter with a precision of approximately 0.10 mm (versus 0.05 mm for the dedicated ophthalmological pupillometer used for reference). Consequently, the Tobii® 1750 (a previous-generation eye tracker capable of 50 Hz operation) proved to be an adequate tool for estimating cognitive workload based on pupil dilation/constriction [24].

In the Tobii® T60, the eye tracking sensor unit is integrated into a 17 inch flatscreen monitor. The sensor is also available as a stand-alone system for eye tracking studies involving real-life objects (the participant's approximate field of view is simulated by an external camera mounted close to his or her head), the X60. As the name suggests, the Tobii® T60 and X60 Eye Trackers operate at a frequency of 60 Hz (i.e. one point of data for every ~17 ms); for applications requiring even greater precision, the T120 and X120 models are also capable of 120 Hz operation.

The Tobii® Eye Tracker is designed to be used in conjunction with the proprietary Tobii® Studio Software Package, which allows for the use of a variety of visual stimuli – static pictures, movie files, web pages or software applications, as well as external video sources. Also integrated are tools for the visualization and statistical evaluation of the experiment data. By aggregating the individual data points into fixations using filtering algorithms, the data becomes easier to visualize and more manageable in terms of size and processing power requirements; furthermore, outliers can automatically be identified as such and discarded. Both the filtered and the raw data can easily be exported for evaluation in other programs, such as Statgraphics, Senstools, SPSS or Excel.

Perhaps the most visually striking and intuitively interpretable graphical visualization method is the heat map [31], in which the user's point of gaze "heats" up the parts of the picture it is focused on. The cumulative "heat" is then visualized in a colour scheme similar to that of an infrared camera – the most “interesting” (i.e. the most often- and/or intensely looked-at) parts of the picture appear “red-hot”, while less interesting parts appear from yellow to green. This method produces even more meaningful results when utilizing the cumulative data from several test subjects. While producing results that can be interpreted “at a glance” even by laymen, the heatmap is by no means a replacement for a detailed statistical evaluation. It can, however, be extremely useful for finding “hotspots” on the image that are then used as the basis for “Areas of Interest” (AOIs), based on which statistically analyzable parameters may be calculated (see below). Tobii® Studio is also capable of automatically grouping areas with a high density of fixation points in multiple recordings into “clusters”, which can then be converted into AOIs automatically.

The other main visualization techniques are the gaze replay and gaze plot, in which the fixation points are represented by circles whose radius corresponds to the length of the fixation, connected by lines representing the saccadic movements. While the gaze replay is a real-time animation that can be exported as a movie file, the gaze plot presents a static image in which the order of the fixations is represented by a number. Both are useful for generally analyzing the gaze patterns of a single person, as well as verifying the quality of a recording, providing clues to questions such as “did the person correctly understand the instructions?”, “did they try to consciously control their gaze patterns?”, “were they distracted by background noise at a certain point during the experiment?”, “is there a drift because the person may be unconsciously shifting positions over the course of the recording” or “did the recording data become corrupted after a software crash?”.

With a “bee swarm”, the gaze plot data for multiple recordings can be displayed simultaneously, providing an intuitive visualization tool for animated stimuli as well as a method of indicating trends in the temporal shifts of attention in a stimulus.

In order to create heatmaps, gaze plots or AOIs (and thus allow a meaningful statistic analysis) for animated stimuli, they can be divided into scenes, i.e. a segment of the recording represented by a still image onto which the visualization tools and AOIs can be drawn. Naturally, the effectiveness of this method is still limited if the relative position of the relevant object on the screen keeps changing, and the segments and scenes have to be carefully edited so as to be sufficiently representative.

2.1.1 Important parameters of Eye Tracking in Tobii® Studio

Eye tracking data is commonly analyzed in form of several variables Tobii® Studio generates from the raw data based on (user-adjustable) fixation filters and user-defined Areas of Interest.

- **First Fixation Duration**: The duration of the first fixation within a specific AOI.
- **Fixations before**: The number of fixations before first fixating within a specific AOI.
- **Time to First Fixation**: Time elapsed between the appearance of a picture and the user first fixating his gaze within an area of interest.
- **Fixation Length**: Length of a fixation within an AOI.
- **Fixation Count**: Number of fixations within an AOI.
- **Observation Length**: Time elapsed between the user's first fixation within a specific AOI and the next fixation outside the AOI.
- **Observation Count**: Number of "visits" to an AOI.
- **Fixations before**: Number of fixations before the user first fixates inside the AOI.

(The following four parameters were not used for this thesis):

- **Participant%**: The percentage of participants that fixated at least once within a given AOI.
- **Time to fixation from click**: The time elapsed between a mouse click and a fixation.
- **Time to first mouse click**: Time elapsed between the appearance of an image and the user's first mouse click.
- **Mouse click count**: Number of mouse clicks.

Tobii® Studio can display the median, mean, summary, maximum and minimum values for these parameters, as well as the standard deviation. For this paper, the summary values were used. Note that while the summary values of "Observation Length" and "Fixation Length" are expected to be somewhat similar, using the mean or median values could produce drastically different results. One should thus make sure that the "Cell Values" button in the statistics window is set to the correct option.

2.1.2 Tobii® Studio Software User Interface

The following screenshots are intended to showcase the principal features of Tobii® Studio used in this experiment. Note that this is by no means a comprehensive overview of the features of Tobii® Studio. For more detailed explanations of the features described herein as well as other capabilities of the Tobii® system, please refer to the Tobii® Studio manual [31]. For an overview of the technological background and capabilities of the device as well as potential applications, refer to the Tobii® White Paper [28].

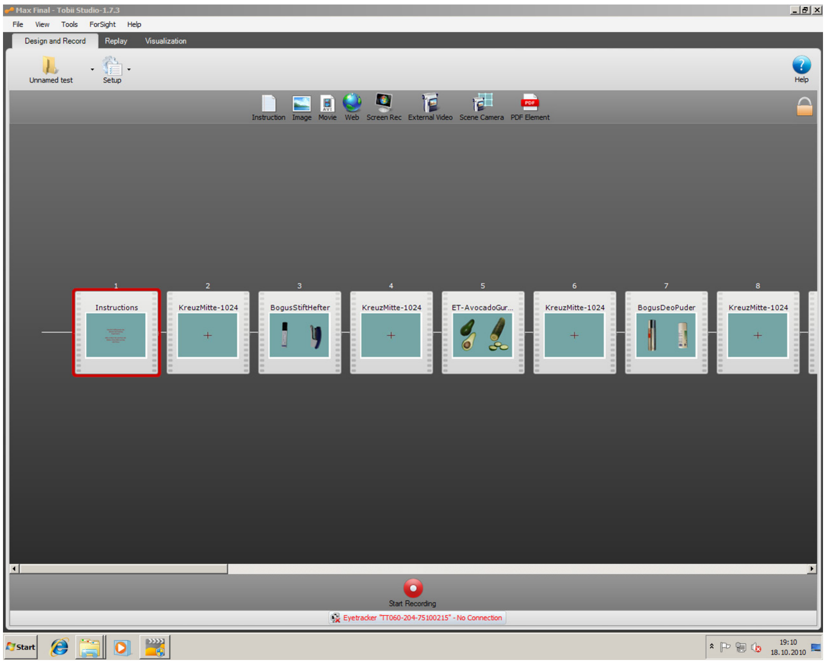

Fig. 3: Tobii® Studio Interface: “Design and Record” screen

In the “Design and Record”-screen, a sequence of visual stimuli can be defined by simply dragging & dropping them into the row at the center of the screen. Double-clicking an element icon opens the properties window, allowing the user to change the file address or set the display time (a specific duration in milliseconds or until a user input either by mouse click or key press).

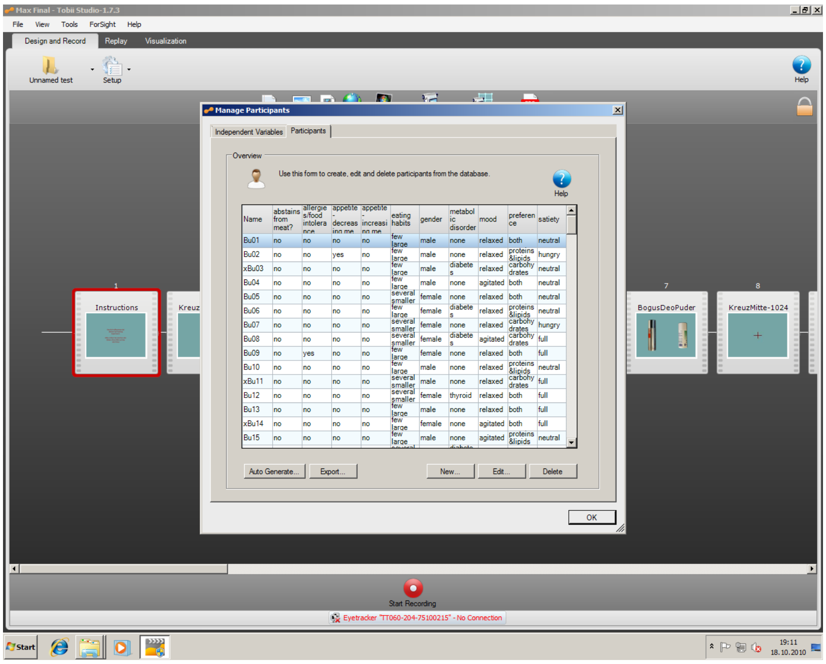

Fig. 4: Tobii® Studio Interface: Participant Management screen

Tobii® Studio presents a simple participant management system. By defining a set of independent variables and the corresponding values, one can have the participant fill out an electronic questionnaire directly before the test (although we found that it was generally advisable to have them fill out the questionnaire on paper and have the operator enter the data later, allowing for a higher participant throughput and preventing the participant from drawing conclusions on the purpose of the experiment based on the questions asked). The independent variables can also be used to create filters to quickly generate visualization options for specific groups. There are, however, limitations to this system, which will be expounded further down this paper.

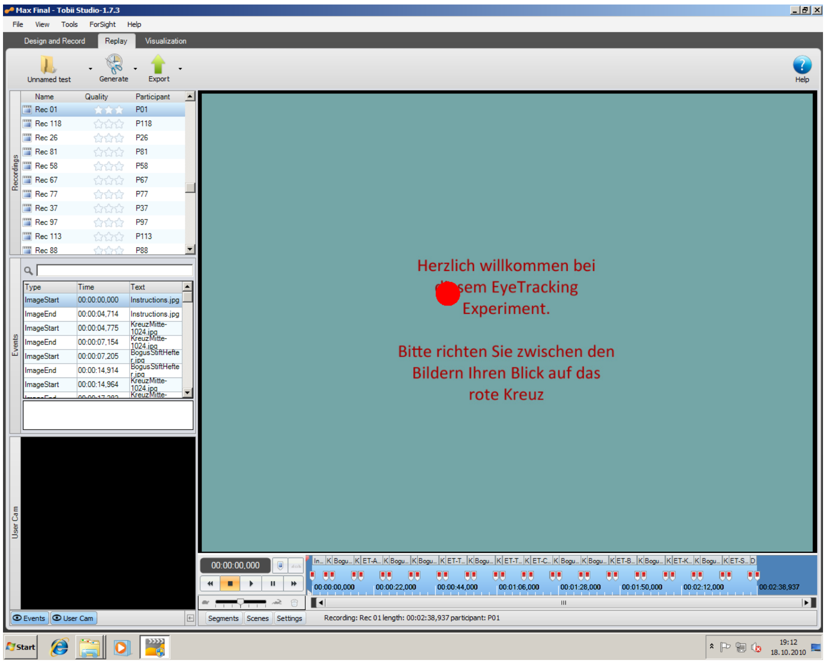

Fig. 5: Tobii® Studio Interface: Replay View

The Replay View is used to provide a dynamic gaze replay (with adjustable playback speeds), group the data into segments and scenes and to export the gaze data in either graphic or text form. The black square in the bottom-left corner is reserved for the user camera (using footage from an external camera, the eye-tracking analysis can be supplemented by an analysis of the test subject’s facial expressions or body language).

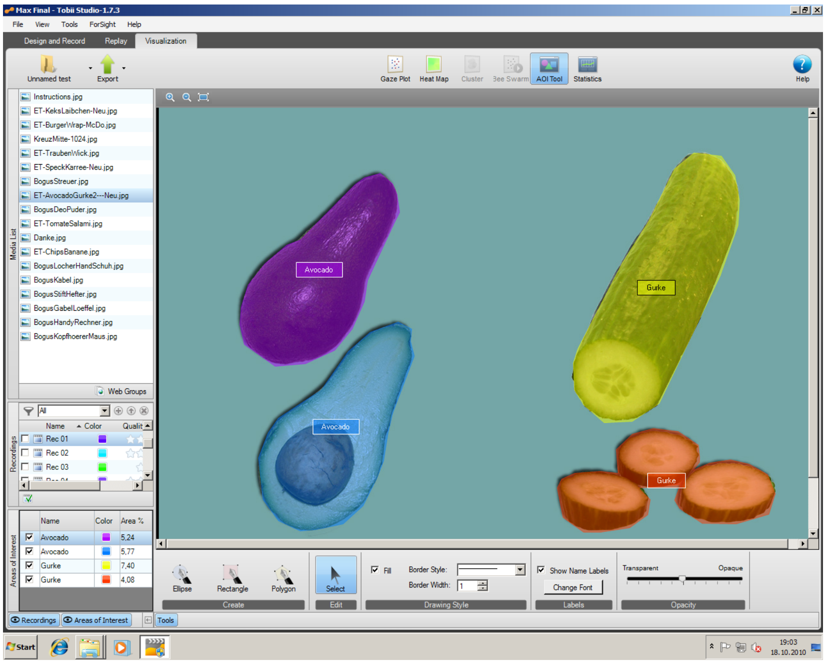

Fig. 6: Tobii® Studio Interface: Visualization View

The Visualization View contains tools for the aforementioned visualization methods (heatmap, gaze plot) as well as the AOI tool (pictured above) that is a prerequisite to a meaningful statistical interpretation of the data. The bar on the bottom contains tools for creating, adjusting and displaying Areas of Interest, which are listed in the bottom left corner of the screen. The percentage of the total image area encompassed by each AOI is also listed. As can be seen here, multiple Areas of Interest can be assigned the same name, so that they count as a single AOI for the statistical evaluation. However, as of Tobii® Studio version 1.7.3, we encountered issues associated with applying the parameter “Fixations Before” to such merged AOIs (see the appropriate chapters in the Results section).

3 Hunger, Obesity and Eating Disorders

3.1 Causes and Cures?

Situated at the very base of Maslow's pyramid, hunger is a feeling that the human mind cannot afford to ignore for long, lest it risk the deterioration and eventual death of the body. Yet as the technological advances of human civilization provide us with an ever-increasing abundance of available foods while simultaneously depriving us of the necessity to expend our newly-acquired energy, we find that the metabolic point of equilibrium our hunger drives us towards is no longer a "healthy" one – if, indeed, it can be considered an equilibrium at all.

In 2008, the cost of obesity-related illnesses in the United States amounted to approximately 147 billion dollars [32], or almost 10% of all medical spending. Obesity has become an epidemic that modern medicine often seems incapable of even treating the symptoms – perhaps because we often fail to recognize that obesity itself is often a symptom of an underlying physical or mental condition.

At the same time, the opposite end of the eating disorder spectrum has also been thrust into the spotlight: Anorexia is defined by the DSM-IV-TR[2] as an eating disorder in which the patient – although already at 85 % or less of his or her expected body weight – experiences an intense fear of being overweight and a distorted body image, and/or he or she may be in denial about the extent of their weight loss and possible physical consequences. In females, an absence of menstruation is also a strong diagnostic indicator (however a wide range of physiological tests - such as blood counts, urinalysis, EEG, ECG, thyroid screening or liver function test - is commonly used to confirm the diagnosis and/or assess potential damages). Anorexia can be of either the "purging" or "restricting" type, depending on whether the individual engages in "purging" behaviors (i.e. induced vomiting or defecation) or not. Although first described in 1879, increasing media coverage of celebrity anorexics, including highly publicized deaths and hospitalizations, have only recently somewhat removed the social stigma and taboo status from this illness. Still, the actual prevalence of anorexia is likely significantly larger than the currently reported 0.3 % (for young females) [33]. Perhaps ironically, the media is also considered by the general public to be a major driving force behind many cases of anorexia – promoting an unhealthy ideal of thinness through film and fashion. Yet there is growing evidence that anorexia can be promoted by a variety of neurochemical factors, and is often hereditary.

Bulimia nervosa, first described in 1979 by Gerald Russell [34], is currently estimated to affect approximately 1% of all young females and 0.1 % of young males [33]. Behaviorally, it

[2] "Diagnostic and Statistical Manual of Mental Disorders, 4th Edition, Text Revision", the American Psychiatric Association's manual for the classification of mental disorders

is characterized by uncontrollable food binges followed by attempts at “compensation” – through induced vomiting, defecation or urination (“purging type”), excessive exercising and/or fasting (“non-purging type”) or both. While this allows many sufferers to effectively maintain a normal body weight and thus the condition to go undiagnosed, it nevertheless takes a significant toll on the body – common symptoms include dental erosion from stomach acid, gastrointestinal reflux, stomach ulcers, esophagitis and swollen salivary glands. In extreme cases, the disturbed electrolyte levels can result in death through cardiac arrest.

Brain imaging studies have found alarming similarities in the brain chemistry of drug addicts and sufferers of eating disorders [6]. Similar to how drug addiction often starts out as a short-sighted attempt at self-medication, food may effectively become a substance of abuse in the obese or bulimic. This theory is supported by the significant comorbidity between eating disorders and mental illnesses. A study by Blinder et al. [35] found that out of 2436 patients treated for bulimia, anorexia or combinations thereof, 97% exhibited one or more comorbid diagnoses: 94% were suffering from mood disorders, 56% from anxiety disorders and 22% from substance abuse disorders.

While modern psychiatric medication has become significantly more specific in its effect (at least when compared to the dire and often permanent side-effects of yesteryear’s drugs), iatrogenic weight gain has become a major cause for concern and the subject of costly lawsuits - as of 2009, Eli Lilly & Co. has had to pay roughly 1.2 billion dollars in settlements in over 32,000 civil cases concerning their best-selling atypical antipsychotic, *Zyprexa*® (olanzapine), of which it had long tried to systematically downplay the risks of massive weight gain and related diabetic illnesses. In fact, a variety of psychotropic medications – mood stabilizers, antidepressants, anxiolytics, sleep aids, tranquilizers and others – are plagued by similar effects on body weight, despite greatly differing in their modes of action. The obese patient may thus find herself trapped in a vicious cycle – improvements in mood may be offset by a loss of self-esteem and decreased physical and social activity resulting from the higher body weight. In extreme cases, patients may attempt to regulate their weight by adopting bulimic behaviors. Often additional psychotherapy [36] or augmentation with other, weight-loss related drugs [37] may become necessary.

The fact that none of the substances typically used in such cases - like the antidepressant bupropion (*Wellbutrin*®) or the anticonvulsant topiramate (*Topamax*®) – are actually approved as weight loss aids (instead being prescribed “off-label” for a “desirable” side effect) showcases the need for effective weight loss drugs.

Also striking is that topiramate – despite its efficacy for many clinical applications (including obesity, particularly when related to binge eating disorder [38]) – is barely understood in its pharmacology. Putative mechanisms include a “blockade of conditioned and automatic processes” via antagonism at the AMPA receptor [39] as well as inhibition of the human mitochondrial carbonic anhydrase [40]. The latter explanation also accounts for the anorectic effects of the pharmalogically related zonisamide [41], which is currently being developed under the name “Empatic” as a weight loss drug in a sustained-release formulation combined with bupropion [42].

Bupropion is a unique antidepressant acting as a noradrenaline-dopamine reuptake inhibitor, partially suppressing hunger by increasing the synaptic concentrations of these neurotransmitters (see below for a more detailed explanation). Despite being structurally related to stimulants such as cathinone, bupropion does not cause euphoria, theoretically carrying less abuse liability than caffeine [43]. Bupropion is also a nicotinic acetylcholine receptor (nAchR) antagonist [44], and as such is used as a smoking cessation aid (thus helping to reduce weight gain associated with nicotine withdrawal). The general antiaddictive nature of nAchR antagonists [45] may also explain its anorectic effect when assuming an addiction-like model of eating disorders. Risks of bupropion treatment include a lowered seizure threshold (which may be compensated by combining it with an anticonvulsant such as topiramate or zonisamide [46]; see above [42]) and the triggering of psychotic episodes in susceptible individuals [47].

Obesity and related eating disorders represent a vast but largely untapped pharmaceutical market. The number of drugs that tried and failed – often with catastrophic results – to remedy this condition reminds us that in order to develop a tolerable anorectic with sustainable effects, we first need to understand the complex interplay of neural signaling pathways that govern our feeding habits.

3.2 The Neurobiology of Hunger

3.2.1 Dopamine

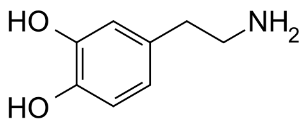

Fig. 7: 2D structure of dopamine [48]

The “incentive sensitization” [49] theory is a psychological model proposing a common psychological explanation for the addictive mechanism of a wide range of drugs, which has also been applied as an “addiction model” of obesity. The basic principle is that intake of the “drug” (or in this case food) triggers a sensitization in the reward-related mesolimbic dopaminergic pathway of the brain, increasing the salience of reward-related cues – in other words, food-related cues become more “attention-grabbing” and likely to trigger cravings, which in turn increases overall food intake and promotes further sensitization, effectively creating a vicious cycle. The effects of this sensitization are extremely long-lasting; even after months of abstinence (long after any effects of physical withdrawal are gone), confrontation with a drug-related cue may trigger a relapse. PET scans on dopamine receptor levels have shown similar decreases in the striata of pathologically obese patients and stimulant addicts [6].

The dopaminergic system thus seems like a logical target for the pharmacological treatment of eating disorders, although its staggering complexity and often apparently paradox behaviors present a major challenge. For example, the D1 dopamine receptor is thought to play a major role in the underlying mechanisms of long-term sensitization [50], but anorectic effects have been produced both by D1 antagonists [51] (the occurrence of severe dysphoric side-effects may preclude these from being used as a mainstream treatment for obesity [52]) as well as agonists [53-54].

Another interesting paradox is the anorectic effect of dopamine reuptake inhibitors (most notoriously cocaine) and dopamine releasing agents (including the equally notorious amphetamines) – the DRI methylphenidate (“Ritalin”) has been shown to increase “nonhedonic” food motivation by increasing dopamine levels in the dorsal striatum [55], while generally acting as an anorectic by reducing overall energy intake and relative dietary fat content [56]. Similarly, amphetamine has been shown to increase the cue-triggered “wanting” of food rewards [49] despite its overall anorectic effect for which it is still employed on an “off-label” basis [57]. While the euphorigenic properties of these drugs confer an inherent risk of addiction, recent experiences with these drugs in the treatment of Attention Deficit Hyperactivity Disorder have nevertheless shown that responsible medicinal use is possible, especially in extended-release formulations. Tesofensine, a triple reuptake inhibitor (simultaneously blocking the reuptake of serotonin, noradrenaline, and dopamine) structurally related to cocaine (but not sharing its recreational potential) has shown remarkable anorectic effects in Phase II trials [58], although further trials will be needed to rule out potential side-effects, particularly the adverse psychiatric effects that have recently spelled the demise of rimonabant (see below). Mutations in the DAT1 gene encoding the human dopamine transporter have a significant effect on an individual's responsiveness to dopamine reuptake inhibitors, and may also predispose individuals toward certain eating disorders [59].

3.2.2 Serotonin

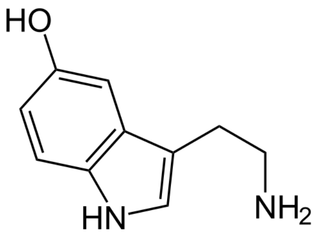

Fig. 8: 2D structure of serotonin [60]

Linked to the dopaminergic system is the neurotransmitter serotonin (5-Hydroxytryptamine) via the 5-HT_{2c} receptor. Activation of this receptor by an agonist (e.g. serotonin) blocks the release of dopamine in the striatum [61], thus regulating appetite and satiety: Food intake results in an increased release of serotonin, which shuts down the dopamine-mediated feeling of hunger. Modern "atypical" antipsychotics such as quetiapine (Seroquel®) and olanzapine (Zyprexa®) largely produce their stabilizing effects through antagonism at this receptor, making it harder for the brain to feel satiated and thus often resulting in significant weight gain. This, in turn, creates an increased risk of cardiovascular conditions and type II diabetes [62]. While this effect would suggest 5-HT_{2C} agonists as potential anorectics, this approach is again fraught with risks. The research drug *meta*-Chlorophenylpiperazine (mCPP), one such agonist, has shown remarkable potential in not only reducing appetite in obese subjects [63], but also increasing insulin sensitivity in animal models of glucose homeostasis, thus presenting a possible first step towards a "cure" for type II diabetes [64]. This research also indicates that the anorectic effects of 5-HT_{2c} agonists strongly depend on their activity on proopiomelanocortin (POMC) neurons; POMC interacts with the melanocortin receptor 4, mutations of which have been linked to autosomal dominant obesity [65]. Unfortunately, mCPP is also a "dirty drug" with a variety of psychotropic side effects and a strong tendency to induce migraines [66]. Another 5-HT_{2c} agonist, lorcaserin, was originally projected to be commercially marketed as an anorectic in 2010, having successfully completed phase III trials without increasing the risk of adverse psychiatric or cardiovascular reactions in patients, the only statistically significant adverse effect being the triggering of headaches in migraine-prone patients [67] (on October 23rd, 2010, the American FDA issued a letter stating they could not approve the drug in its present form, citing uncertainties regarding the emergence of tumors in animal studies [68]).

Another approach to agonizing the 5-HT_{2c} receptor is to increase the level of available serotonin in the synaptic cleft either by inhibiting the reuptake or promoting the release of serotonin. The former approach is taken by the newer anorectic sibutramine (Reductil®, Meridia®), a serotonin-noradrenaline reuptake inhibitor. Originally intended as an antidepressant, it failed to show clinical efficacy for this application, and was repurposed as an anorectic due to the high incidence of weight loss as a side-effect [69]. In addition to the psychiatric side effects sometimes encountered with SNRI-type antidepressants, sibutramine was also found to confer an increased risk of cardiovascular diseases, leading to it being taken off the Italian market in 2002 and prompting the European Medicines Agency to recommend its removal from European markets in 2010 [70]. Despite these problems, there is a significant demand for sibutramine on the black market, both sold as counterfeit medical products and as the active component of fraudulent “herbal” weight loss products, often in amounts far exceeding the medically recommended dose [71].

Serotonin releasing agents such as fenfluramine actively promote the release of serotonin by disrupting vesicular storage of serotonin and/or reversing the action of the serotonin transporter. While effective for this purpose, fenfluramine and its metabolites were also found to be agonists of another type of serotonin receptor, the 5-HT_{2b} receptor, which mediates the cardiopulmonary effects of serotonin, and is thus largely found in the heart valves. Long-term use of fenfluramine was thus associated with a greatly increased risk of developing heart valve conditions such as cardiac fibrosis [72], leading to its removal from US markets in 1997. Wyeth, maker of the fenfluramine-phentermine combination product Fen-Phen, was faced with more than 50,000 product liability lawsuits, setting aside a sum of 21.1 billion US dollars to cover the cost of the settlements [73].

Interestingly, phentermine, the other active component of Fen-Phen, may soon be making a comeback as a weight loss drug. As a noradrenaline releasing agent, phentermine is devoid of any significant serotonergic agonist activity and thus does not increase the risk of heart valve disease. Qnexa, a combination of phentermine and the anticonvulsant topiramate (which itself possesses a modest anorectic effect) has already demonstrated significant clinical benefit in Phase III clinical trials [74].

A dysregulation of the serotonergic system has also been proposed as an explanation for anorexia nervosa – dietary restriction results in a reduced uptake of tryptophan into the brain and thus reduced synthesis and release of serotonin, which in turn reduces anxiety. While the exact mechanism behind this has not been fully elucidated, a reduction in serotonin levels may serve to improve mood by producing an eventual upregulation of postsynaptic serotonin receptors [75], forcing the anorectic to continue dieting to avoid a resurgence of dysphoric symptoms. The profound effect of female gonadal hormones on the serotonergic system [76] may also provide an explanation for why eating disorders usually manifest during adolescence, although it should be noted that characteristic personality traits associated with these disorders (anxiety, perfectionism) usually are already evident during childhood [77].

3.2.3 GABA

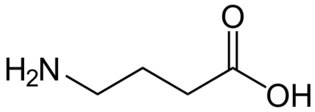

Fig. 9: 2D structure of γ-amino-butyric acid (GABA) [78]

Another neurotransmitter implicated in the regulation of hunger and feeding is the inhibitory neurotransmitter γ-amino butyric acid (GABA). Responsible for the mediation of mental and physical relaxation, GABAergic drugs play a major role in the short-term treatment of psychological agitation, anxiety disorders or insomnia, despite their often significant addiction potential.

Perhaps the most important GABAergics in clinical use today are the benzodiazepines, a family of anxiolytic, hypnotic and muscle relaxant drugs acting as allosteric modulators of GABA receptors with an extremely broad therapeutic window (the LD50 of benzodiazepines is hundreds or thousands of times greater than the therapeutic dose, allowing them to be safely prescribed even to outpatients with suicidal ideation). As a more recent development, benzodiazepines are facing competition in the sleep aid market by the so-called “non-benzodiazepines” or “Z-drugs” (zolpidem, zopiclone and zaleplon) which promise a lower abuse potential and risk for addiction due to a greater specivity for the α1-subunit of the $GABA_A$-receptor which is responsible for the hypnotic effect.

Interestingly, the α1-subunit is also primarily responsible for the orexigenic effect of these drugs [79]. The combined orexigenic, disinhibiting and amnestic properties of this receptor can thus lead to iatrogenic eating disorders in which a patient treated with Z-drugs experiences somnambulic food binges which he often has no recollection of on the morning after [80].

Certain gene sequence variants which increase overall GABA concentration, such as the GAD2 gene coding for the enzyme glutamate decarboxylase (which catalyzes the formation of GABA from glutamate) have since been shown to predispose their carriers towards greater weight gain [81].

The connection between GABA's orexigenic and sedating properties may preclude the development of GABA antagonists or inverse agonists as anorectics [82], as the anorectic benefit of these compounds would be coupled with an increased risk of elevated anxiety levels, insomnia and seizures [83].

3.2.4 Neuropeptide Y

The primary mechanism behind the orexigenic effect of GABA seems to be its effect on orexigenic NPY neurons in the paraventricular nucleus [81]. Neuropeptide Y is a 36-amino-acid polypeptide neurotransmitter with minor effects on stress resilience, seizure prevention and memory retention, but its primary purpose seems to be to induce hunger and decrease energy expenditure [84]. Increased expression of NPY has been shown to correlate with obesity in animal models [85], as well as both anorexia nervosa and bulimia nervosa [86].

Four types of G-protein coupled NPY receptors have been identified in humans to date [87], with Y_1 and Y_5 promoting feeding behavior and Y_2 and Y_4 inhibiting it. Consequently, anti-obesity effects could be achieved either by agonizing the Y_2 and/or Y_4 subtypes or antagonizing the Y_1 and Y_5 subtypes.

The first clinical trial of an NPY ligand, the Y_5-specific MK-0557, failed to produce "clinically significant weight loss" [88]. Peptide $YY_{3\text{-}36}$, a homologue of Peptide Y and an endogenous agonist at the Y_2 subtype, has been evaluated as an anorectic in obese humans, decreasing food intake when administered intravenously, with nausea as a side effect at higher doses [89], but showing no efficacy in a nasal spray formulation [90]. Obinepitide (TM-30338), an agonist at both the Y_2 and Y_4 receptors has been shown to reduce food intake in phase I and II clinical trials in a once-daily subcutaneous injection [91-92]. Lu AA33810, a specific Y_5 antagonist, has demonstrated antidepressant, anxiolytic and anorectic effects in rats, theoretically presenting an ideal pharmacological profile for the treatment of eating disorders [93].

Commercial success of these compounds in the treatment of obesity is likely to depend on whether a convenient (e.g. oral, transdermal or intranasal) form of application can be developed; also, extensive clinical trials will most likely be necessary to rule out adverse psychiatric effects seen in some NPY ligands [94].

3.2.5 Cannabinoids

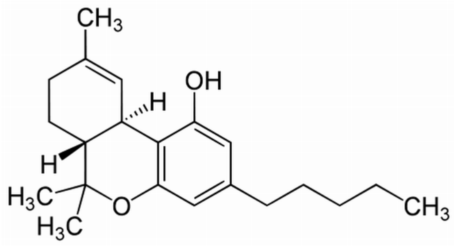

Fig. 10: 2D structure of delta-9-tetrahydrocannabinol („THC“) [95]

The plant *Cannabis sativa* contains a multitude of psychoactive compounds, most prominently delta-9-tetrahydrocannabinol („THC“), that exert a powerful anxiolytic, analgesic, antiemetic and orexigenic effect. While the latter may be undesirable to recreational users, this effect has been exploited therapeutically since antiquity, and today makes it an ideal candidate for the treatment of conditions associated with chronic pain and weight loss, such as AIDS and various forms of cancer.

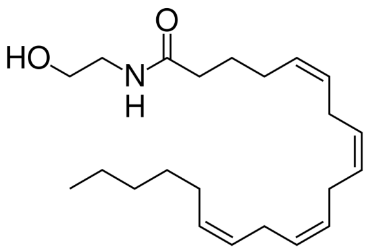

Fig. 11: 2D structure of the endogenous cannabinoid ligand, anandamide [96]

The targets for these compounds are the cannabinoid receptors, a family of G-protein coupled receptors with CB_1 (primarily located in the brain and responsible for the orexigenic action) and CB_2 (found primarily in the immune system) as its currently known members. The endogenous ligands for these receptors are a family of long-chain lipid derivatives, the endocannabinoids, most notably anandamide (arachidonoylethanolamine) and 2-arachidonoylglycerol (2-AG).

Sufferers of anorexia nervosa and bulimia nervosa show a significantly increased expression of CB_1-mRNA [97], and both anorexia nervosa and binge eating disorder are associated with higher blood levels of the endocannabinoid ligand anandamide [98]. Obesity has been linked to lower expression of CB_1 receptors as well as the endocannabinoid-degrading enzyme fatty acid amide hydrolase (FAAH), leading to a higher concentration of anandamide and 2-AG in visceral adipose tissue [99].

Given the appetite-increasing effects of cannabinoid agonists, CB_1-receptor antagonists seemed to be ideal candidates for a novel class of non-stimulant anorectics. Thus SR 141716 (later known as rimonabant), a specific inverse agonist at the CB_1 receptor, was quickly chosen for development as a weight-loss drug. While initial results were promising

[100] and the product was eventually marketed under the name „Acomplia“ in European markets in 2006, reports of depression, anxiety and suicidal ideation (given the euphorigenic “side”-effect of THC, an inverse agonist at the same receptor is likely to cause the opposite, i.e. dysphoria) in patients led to rejection of the drug by the American FDA in 2007 [101] and its official removal from European markets in 2009; at this point, the development of several other CB_1-antagonists/inverse agonists had already been aborted. Should the development of cannabinoid-based anorectics be resumed, the risk of psychiatric side-effects would have to be minimized, for example by primarily targeting receptors outside the central nervous system, providing a better balance of agonist/antagonist/inverse agonist effects, or acting indirectly by modulating the enzymatic formation/breakdown [102] or reuptake [103] of the body’s endogenous cannabinoid ligands [104].

3.2.6 Opioids

Again related to an “addiction model” of eating disorders is the use of opioids in their treatment. In rat models, a diet involving alternating periods of food deprivation and excessive intake of glucose produced a sensitization of D1 dopamine receptors (see chapter “dopamine” for an overview of incentive sensitization and the role of dopamine in feeding) and μ-opioid receptors in the brain [105], producing a state similar to morphine addiction in which treatment with naloxone precipitated withdrawal symptoms [106], suggesting that “sugar addiction” may after all be a legitimate medical condition [107].

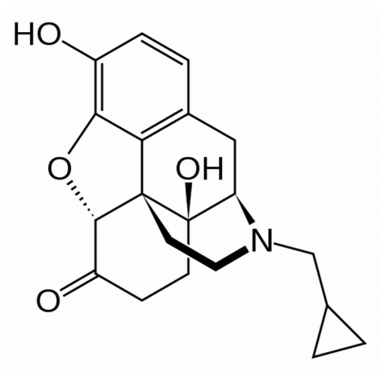

Fig. 12: 2D structure of the opioid antagonist naltrexone [108]

Naltrexone (not to be confused with naloxone) is an opioid antagonist used primarily in the treatment of opioid addiction, although it has been shown to facilitate abstinence in a wide range of substance abuse disorders, such as alcoholism [109] or cocaine dependence [110]. Given the above parallels between eating disorders and drug addiction, the efficacy of naltrexone in conditions such as binge eating disorder [111] and bulimia [112] comes as no surprise, especially considering how naltrexone also attenuates symptoms of borderline personality disorder [113] which shares a significant comorbidity with these disorders.

Naltrexone has been used “off-label” for these purposes for over two decades, and “Contrave”, a dedicated naltrexone-based anti-obesity drug is currently undergoing phase III clinical trials [114]. Combining sustained-release formulations of naltrexone and bupropion (see above), the developer claims that “bupropion helps initiate weight loss while naltrexone may sustain weight loss by preventing the body’s natural tendency to counteract efforts to lose weight” [115]; additionally, the antidepressant effect of bupropion may address comorbid depressive symptoms.

3.3 Addendum

While there is currently a major research effort toward drugs for the treatment of obesity and/or binge-eating disorder, there are no dedicated anti-anorexia agents in the development pipeline. Reasons for this might be the comparatively small target demographic, as well as the fact that most current antipsychotics and a number of antidepressants increase appetite [36] while addressing the mood disorders that almost invariably accompany this condition [35]. While selective serotonin reuptake inhibitors (SSRIs) have demonstrated efficacy in reducing bulimic symptoms, they do not seem to be effective in malnourished anorexia nervosa patients, likely because of the serotonin-depleted state of the patient; they do, however, significantly reduce the rate of relapse after remission [116].

4 Materials and Methods

4.1 Materials

4.1.1 Hardware

- Tobii® T60 Eye Tracker
- Canon EOS 400D digital camera with a Canon EF-S 18-55 lens
- Interfit Photographic Photobox
- 2 Interfit Stellar Tungsten 500 Studio Lamps (Colour Temperature 3200K)
- DiTech dimotion Fastbook F7B4 (laptop equipped with eye tracking software)
- Toshiba Satellite A100-733 laptop (personal laptop for data analysis)

4.1.2 Software

- Tobii® Studio 1.7.3 Software
- StatPoint STATGRAPHICS® Centurion XV v. 15.2.11 (statistics)
- Microsoft® Windows Vista Home Premium
- Microsoft® Word 2007 (word processing)
- Microsoft® Excel 2007 (spreadsheets)
- Adobe® Photoshop® CS4 Extended (composing and editing of images)
- IrfanView v. 4.2.7 (resizing and resampling of images)

4.2 Visual Stimuli

Images for the visual stimuli were photographed using a Canon EOS 400D digital camera or adapted from the department's archive of stock photos and images taken during the course of previous diploma theses. To achieve optimum quality, we experimented with different backdrops and lighting conditions – a blue velvet backdrop, for example, provided optimum contrast (and thus easy manipulation in Photoshop), but also resulted in a bluish tint because of light reflected off of or passing through the backdrop; artificial lighting produced optimum illumination of the object, but resulted in a slightly reddish tint.

Adobe Photoshop CS4 Extended was then used to crop, adjust and analyze the images, and match them into pairs of similar size, colour, visual complexity and brightness.

While photographic backgrounds (a dinner plate and a desk pad) were temporarily considered, we eventually settled on a uniformly light blue background for a more standardized look and optimum contrast.

As in previous eye tracking experiments on this department, a fixation cross was briefly shown in between stimuli as a means to normalize gaze positions. However, by evaluating the full gaze data from these experiments, we found that the previously used brightly-colored cross in front of a pitch black background (i.e. a very dark image overall) resulted in a dilation of the pupil, followed by constriction when viewing the bright blue backgrounds of the stimulus images. To reduce the interference from fluctuations in pupil size and to minimize eye strain, we consequently decided to use an identical background colour for the fixation cross and the test stimuli. Furthermore, we decreased the brightness of the background (trying to achieve a similar overall brightness for all parts of the image) since an excessively bright background made the food items appear dull and grayish in colour and produced increased eye strain.

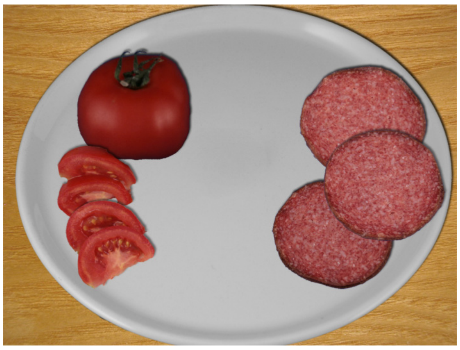

Fig. 13: Early version of a food image with a photographic background

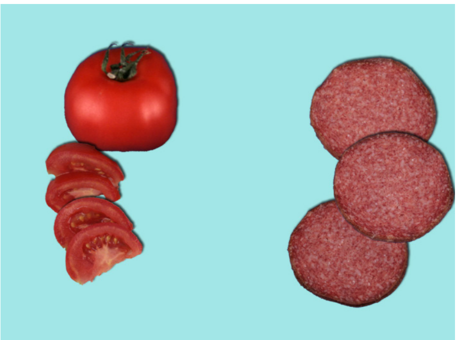

Fig. 14: Same food image with slightly adjusted brightness settings and a bright blue background

Fig. 15: Food image with optimized background brightness

After preliminary testing showed that participants were able to precisely keep their gaze on the fixation cross, the food items were shifted slightly towards the center of the image.

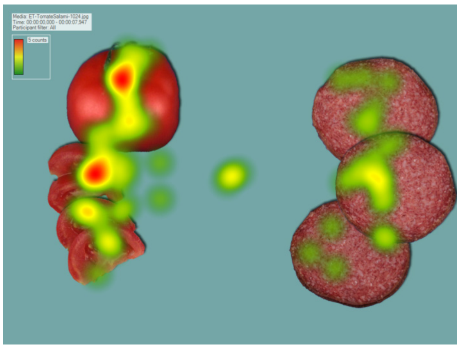

Fig. 16: Heat map of the above image

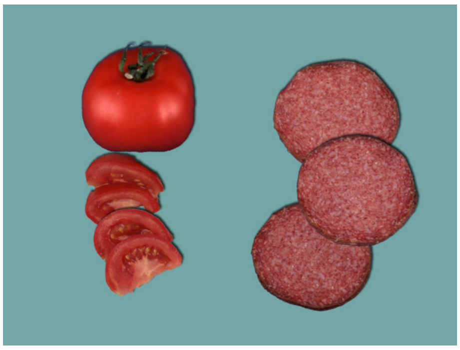

Fig. 17: Finalized version of the above image

In the original version of the image “Burger-Wrap” (Fig. 18), the difference in caloric density was not found to be readily apparent to the common observer, thus new photographs were taken to place more emphasis on components commonly associated with a high caloric content (the grilled patty and cheese) while removing the “healthy” components (lettuce, tomatoes, onions).

Fig. 18: Image comparing a double-patty cheeseburger and a chicken wrap

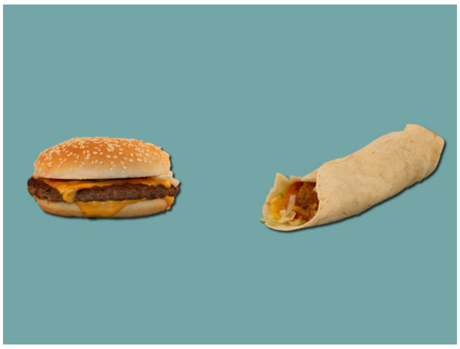

Fig. 19: New image with greater emphasis on visible fat content

Other issues that required modifications to or replacement of parts of the images were errors of scale (fixed by resizing the image in question), small label stickers (removed in Photoshop), pixelation effects due to the poor quality of the source photograph (new photos had to be taken) or that a food item could not be clearly identified (an alternative photo was used).

With some images, we had to find an acceptable balance between what the participant would expect an item to look like and its actual "real-life" appearance. With the Burger King Double Whopper® pictured in Fig. 18, for example, the tomatoes, lettuce and pickles were re-arranged to make them more visible in the photograph, and the bun had to be photographed from an optimum angle to hide the blemishes resulting from being transported while only covered by a thin wrapping paper (some of the higher-priced McDonald's® burgers come in a small cardboard packaging usually allowing for a better shape retention during transport). Similarly, the available photograph of bacon was given a more appetizing appearance by applying slight colour palette adjustments to give it a more appetizing (i.e. reddish) appearance.

While this may seem disingenuous at first, it is reasonable to assume that in such cases, the consumer is strongly influenced in his food purchases (and, consequently, his food consumption) by the idealized appearance projected by advertisements, packaging illustrations or carefully illuminated supermarket meat counters rather than the actual appearance of the item on his plate.

4.3 Finalized images

Fig. 20: Instructions

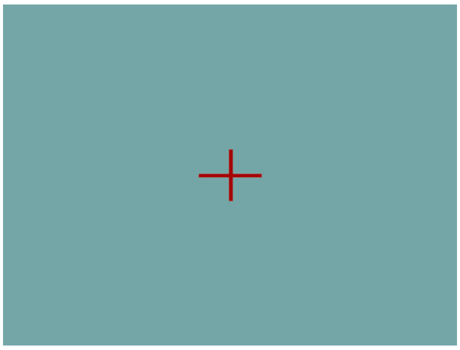

Fig. 21: Fixation cross

4.3.1 Food images

The finalized images used in the experiment are shown below. To the right is the corresponding image with the AOIs overlaid. We attempted to make the AOIs conform to the actual borders of the object as closely as possible (*note: the black borders on the AOI screenshots are artifacts of the screenshot function, and were not visible on the final image*).

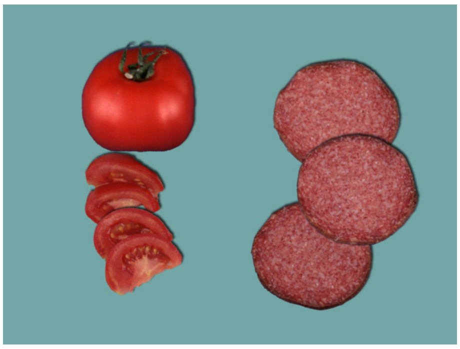

Fig. 22: Tomato & salami

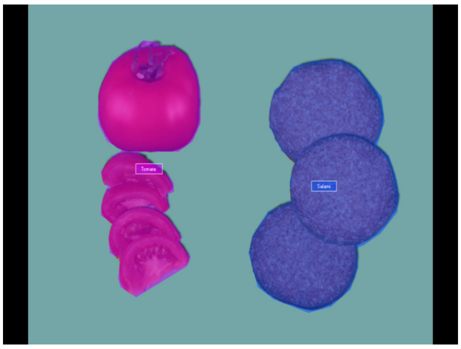

Fig. 23: Tomato & salami (AOIs)

Fig. 24: Avocado & cucumber

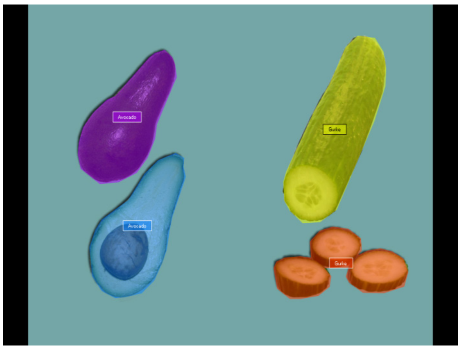

Fig. 25: Avocado & cucumber (AOIs)

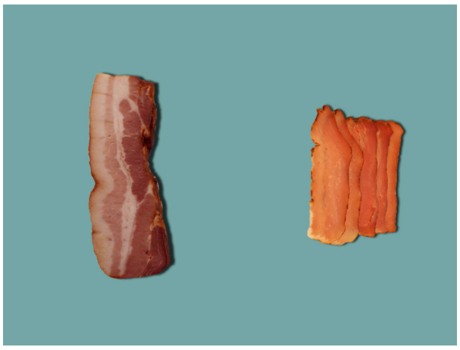

Fig. 26: Bacon & lean pork loin

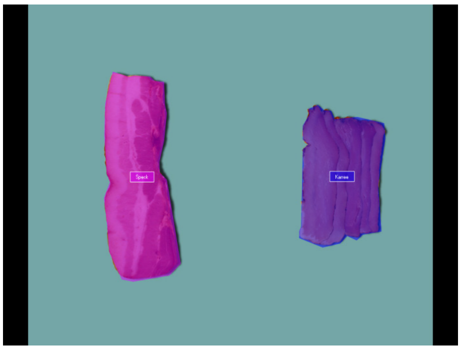

Fig. 27: Bacon & lean pork loin (AOIs)

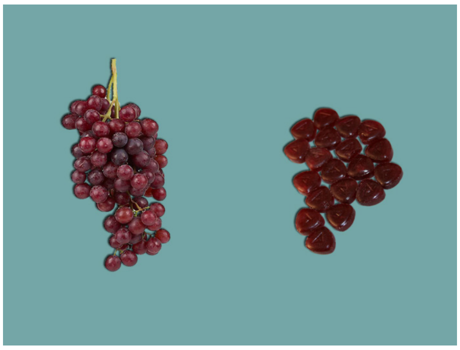

Fig. 28: Grapes & cassis-flavored candy

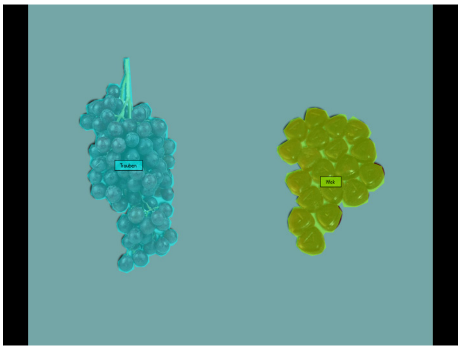

Fig. 29: Grapes & cassis-flavored candy (AOIs)

Fig. 30: Double cheeseburger & chicken wrap

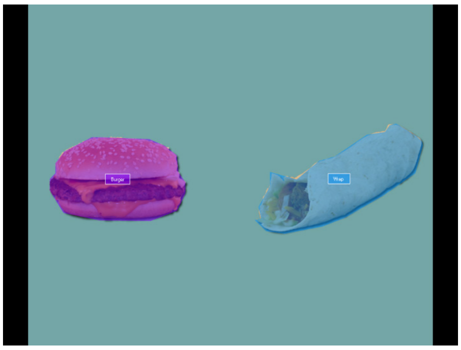

Fig. 31: Double cheeseburger & chicken wrap (AOIs)

Fig. 32: Chocolate-chip cookie & pumpkin seed roll

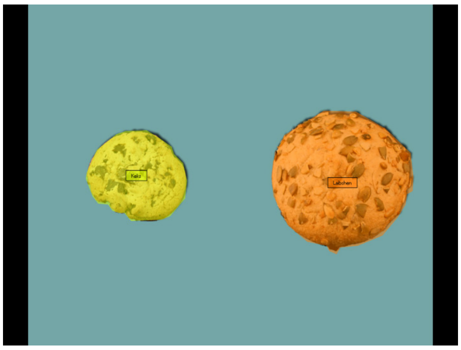

Fig. 33: Chocolate-chip cookie & pumpkin seed roll (AOIs)

Fig. 34: Potato chips and banana chips

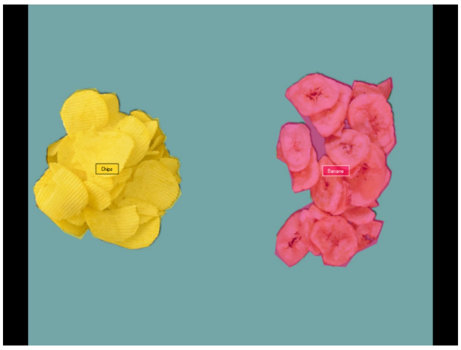

Fig. 35: Potato chips and banana chips (AOIs)

4.3.2 Bogus images

Fig. 36: Deodorant and powder

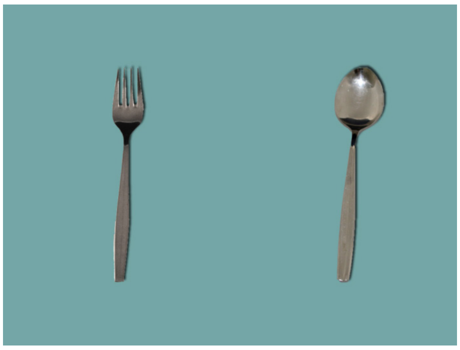

Fig. 37: Fork and spoon

Fig. 38: Cell phone and calculator

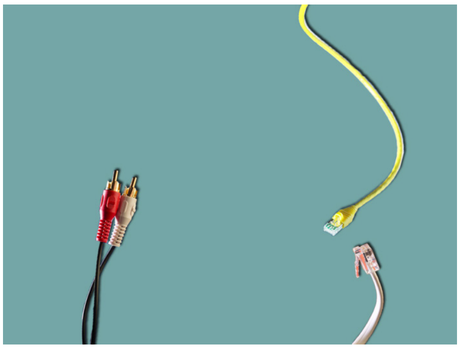

Fig. 39: Cables

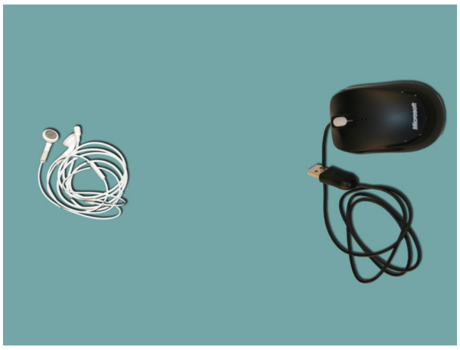

Fig. 40: Earphones and computer mouse

Fig. 41: Hole puncher and glove

Fig. 42: Permanent marker and stapler

Fig. 43: Salt and pepper shakers

4.4 Image sequence

The test was preceded by a German instruction text instructing the participants to direct their gaze to the red fixation cross appearing between the following pictures (*"Herzlich Willkommen bei diesem EyeTracking Experiment. Bitte richten Sie zwischen den Bildern Ihren Blick auf das rote Kreuz"*; see Fig. 20), which was displayed for a duration of 5 seconds. Naturally, English-speaking participants were given the same instructions verbally before the experiment (as were German-speaking participants, in order to rule out potential misunderstandings). Each fixation cross was displayed for 2.5 seconds, while the visual cue images themselves were shown for 8.0 seconds.

The images were displayed in the following order (each preceded by a fixation cross):

Table 1: List of images

image no.	bogus?	Stimulus name	Left item	Right item
1	y		Permanent marker	Stapler
2	n	Avocado-Cucumber	Avocado	Cucumber
3	y		Deodorant spray	Powder
4	y		Hole puncher	Glove
5	n	Tomato-Salami	Tomato	Salami
6	y		Cables	Cables
7	n	Grapes-Candy	Grapes	Candy(cassis flavored)
8	n	Chips-Banana	Potato chips	Banana chips
9	y		Fork	Spoon
10	y		Salt mill	Pepper mill
11	n	Burger-Wrap	Double cheeseburger	Chicken Wrap
12	y		Earphones	Computer mouse
13	n	Cookie-Roll	Chocolate chip cookie	Pumpkin seed roll
14	y		Cell phone	Calculator
15	n	Bacon-Loin	Bacon	Lean loin

(Note that the naming scheme for the stimuli is always "left item – right item".)

4.5 Caloric densities

Table 2: Caloric densities of the foods used for this study. Sources: Original product labels, www.fettrechner.de [117], fddb.info [118], www.mcdonalds.at [119], www.burgerking.at [120].

image	food item	cal. density (kcal/100 g)
Tomato-Salami	Tomato	17
	Turkey Salami	300
Avocado-Cucumber	Avocado	217
	Cucumber	12
Bacon-Lean Loin	Bacon	334
	Lean Pork Loin	151
Grapes-Candy	Grapes	71
	Cassis Candy	227
Burger-Wrap	Cheeseburger	246
	Grilled Chicken Wrap	151
Cookie-Roll	Chocolate Chip Cookie	586
	Pumpkinseed Roll	280
Chips-Banana	Potato Chips	533
	Banana Chips	300

4.6 Participants

The first batch of participants was recruited at the Muthgasse 18 building of the University of Natural Ressources and Life Sciences, some of which approached the laboratory on their own (responding to notices posted in several places across the building), and some of which were recruited by personally approaching them in the lobby. For their participation, they were recompensated by coffee, cake and assorted sweets, which they were free to consume either before or after the experiment.

Obese participants were recruited at the Psychosomatisches Zentrum Waldviertel, Eggenburg and the Therapiezentrum Buchenberg, Waidhofen an der Ybbs. In the latter case, each participant was remunerated with €10.

In total, 174 people were tested, with 161 producing acceptable recordings. Unusable recordings were caused by poor recording quality (a “tracking quality” of less than 75%, meaning that the device was able to locate a person’s eyes 3/4ths of the time), conscious manipulation of the participant’s gaze pattern (e.g. focusing only on a single object or the center of the screen) and software crashes.

Out of the usable recordings, 43 participants qualified as obese (having a BMI above 30). The mean BMI of this group was 40.18, and the highest BMI among these was 69.09.

While we attempted to recruit a gender-balanced set of participants, 92 of the usable recordings were from females and 69 from males (57.14% female, 42.86% male). In the obese group, the ratio was 28 females to 15 males.

The mean age in the obese group was also significantly higher in the obese group (41.86 years) than in those with a BMI below 30 (24.58 years).

For a more in-depth discussion of potential selection biases, see chapter 6.

4.7 Questionnaire

The following questionnaire was used to gather demographic data for a later statistical evaluation. Participants were asked to fill it out after the experiment, so as not be influenced by the questions. Due to a miscommunication, participants at the Therapiezentrum Buchenberg were given the questionnaire before the experiment.

To accommodate non-German-speaking participants, the questionnaire was available in both German and English.

Note that during the course of the experiment, the questionnaire was updated to remove certain ambiguities that were repeatedly brought up by participants when filling out the questionnaire (specifically, the “none”-option was added to the question about metabolic disorders, and “do you abstain from eating meat” was changed to “Do you abstain *completely* from eating meat” to avoid misunderstandings for individuals avoiding only specific types of meat, such as Muslims or Hindus.) The version depicted on the following page is the finalized English version.

Please fill out this form by checking the appropriate boxes. All data is for our statistical purposes only and will be handled anonymously and confidentially.

Gender: ❑ female ❑ male
Age:…….years
Weight: ………. kg
Size:………. cm

Which of these best describes your current mood?

❑ aroused, agitated or nervous ❑ relaxed, tired or exhausted

How would rate your current state of satiety?

❑ full ❑ hungry ❑ neutral

Do you suffer from allergies and/or food intolerances?

❑ no ❑ yes – if so, which?…………………………………………

Do you suffer from a metabolic disorder?

❑ none ❑ diabetes ❑ gout ❑ thyroid disease ❑ other:…………………………

Which of the following food categories do you prefer?:

❑ carbohydrates (sweets, fruit, bakery products, cereals…)
❑ protein & lipids (dairy products, meat, fish, eggs…)
❑ both
❑ neither

Which of these best describes your eating habits?
❑ several smaller meals per day ❑ few large meals per day

Do you abstain completely from eating meat products (for ethical, religious or health-related reasons)?
❑ yes (=I DON'T eat meat) ❑ no (=I eat meat)

Are you currently taking medication that might INCREASE your appetite? (e.g. anti-histamines, Mirtazapine, Zyprexa, Seroquel…)
❑ yes ❑ no ❑ don't know ❑ no answer
Are you currently taking medication that might DECREASE your appetite? (e.g. Efectin, Welbutrin, Topamax)
❑ yes ❑ no ❑ don't know ❑ no answer

Thanks for your participation!

5 Results and Discussion

5.1 Left-Right bias

To evaluate the influence of a direction bias for objects on the left side of the screen, as would be expected from participants hailing mostly from Austria or other countries with a left-to-right writing system, we calculated the ratio of the value for the left AOI divided by that for the AOI on the right.

5.1.1 First Fixation Duration

Table 3: Results of analysis for left/right bias in First Fixation Duration, based on the mean values for each AOI.

	Mean	ratio l/r	p-value
Tomato	0.279	83.95%	0.00774868
Salami	0.332		
Avocado	0.288	78.29%	0.000296185
Cucumber	0.368		
Bacon	0.360	94.22%	0.350092
Loin	0.382		
Grapes	0.396	86.33%	0.0316635
Candy	0.459		
Burger	0.357	58.03%	0.0
Wrap	0.616		
Cookie	0.439	124.71%	0.00356386
Roll	0.352		
Chips	0.353	105.87%	0.3813
Banana	0.333		

In general, the duration of the first fixation tends to be slightly lower on the left side (in 5 out of 7 cases) with statistical significance at the 95% confidence level in all cases except Bacon-Loin and Chips-Banana. A possible explanation would be that the participants tend to start with the left side of the screen (see: “Fixations Before” and “Time to First Fixation”, below), but quickly switch to the next AOI to identify the objects on both sides of the screen. Having identified the right-side AOI, they then take their time to inspect it more thoroughly. The significantly longer first fixation on the cookie (despite being on the left side) may be explained by the small size of the cookie that allows it to be identified and mentally categorized in a single fixation.

5.1.2 Fixations Before

Table 4: Results of analysis for left/right bias in Fixations Before, based on the mean values for each AOI.

	Mean	ratio l/r	p-value
Tomato	2.298	52.48%	0.0
Salami	4.379		
Avocado	0.000	-	-
Cucumber	0.000		
Bacon	2.168	62.43%	0.0000395702
Loin	3.472		
Grapes	1.609	52.32%	0.0
Candy	3.075		
Burger	2.317	83.07%	0.120917
Wrap	2.789		
Cookie	2.025	75.99%	0.00557556
Roll	2.665		
Chips	2.161	68.24%	0.000655707
Banana	3.168		

The number of „Fixations Before“ is always lower for objects on the left side of the screen, at a confidence level of 95% or higher in all cases except Burger-Wrap. Since Tobii Studio has problems calculating the “Fixations Before”-values of combined AOIs, there is no result for “Avocado-Cucumber”.

5.1.3 Fixation Count

Table 5: Results of analysis for left/right bias in Fixation Count, based on the mean values for each AOI.

	Mean	ratio l/r	p-value
Tomato	10.379	139.83%	0.0
Salami	7.422		
Avocado	8.696	110.06%	0.0389102
Cucumber	7.901		
Bacon	8.224	90.93%	0.0453867
Loin	9.043		
Grapes	9.075	123.40%	0.00000613617
Candy	7.354		
Burger	8.348	105.58%	0.239283
Wrap	7.907		
Cookie	5.963	56.80%	0.0
Roll	10.497		
Chips	7.106	61.57%	0.0
Banana	11.540		

There is no clear bias in Fixation Counts for either side of the screen. With the exception of Burger-Wrap, all images show a statistical difference between the means at the 95%

confidence level or above. In case of the image Cookie-Roll, the most obvious explanation for the large discrepancy is that the comparatively small cookie can be completely inspected in fewer fixations than the comparatively large pumpkin seed roll. The discrepancy in the image Tomato-Salami may be explained by the largely homogenous appearance of the salami (three slices of nearly identical-looking sausage) compared to the more complex appearance of the tomatoes (1 whole tomato and 4 slices of tomato).

5.1.4 Fixation Length

Table 6: Results of analysis for left/right bias in Fixation Length, based on the mean values for each AOI.

	Mean	ratio l/r	p-value
Tomato	3.705	137.91%	0.0
Salami	2.686		
Avocado	3.194	108.09%	0.0779265
Cucumber	2.955		
Bacon	2.858	85.00%	0.00019222
Loin	3.362		
Grapes	3.516	118.78%	0.0000112116
Candy	2.960		
Burger	2.888	77.34%	0.0
Wrap	3.734		
Cookie	2.546	66.14%	0.0
Roll	3.850		
Chips	2.520	62.81%	0.0
Banana	4.012		

Again there seems to be no clear bias for the total Fixation Length of objects on either side of the screen, although all images except for Avocado-Cucumber show statistical significance at the 95% confidence level or above. For the image Cookie-Roll, the effect of the smaller area of the cookie is clearly evident, as is the discrepancy between tomato and salami.

5.1.5 Observation Count

Table 7: Results of analysis for left/right bias in Observation Count, based on the mean values for each AOI.

	Mean	ratio l/r	p-value
Tomato	2.795	117.19%	0.00230002
Salami	2.385		
Avocado	7.571	106.46%	0.177783
Cucumber	7.112		
Bacon	2.764	102.30%	0.60401
Loin	2.702		
Grapes	2.932	117.71%	0.000543923
Candy	2.491		
Burger	2.727	100.69%	0.905621
Wrap	2.708		
Cookie	2.739	93.43%	0.185837
Roll	2.932		
Chips	2.596	99.05.%	0.845968
Banana	2.621		

The Observation Count for objects on the left side of the screen is slightly higher, likely because the first fixation (and thus the first observation) is usually on the left AOI, although this can only be statistically verified on the 95% confidence level with the pictures Tomato-Salami and Grapes-Candy.

5.1.6 Observation Length

Table 8: Results of analysis for left/right bias in Observation Length, based on the mean values for each AOI.

	Mean	ratio l/r	p-value
Tomato	3.807	137.56%	0.0
Salami	2.767		
Avocado	2.079	257.95%	0.0
Cucumber	0.806		
Bacon	2.982	83.65%	0.0000314642
Loin	3.565		
Grapes	3.642	119.36%	0.00000695817
Candy	3.051		
Burger	2.987	77.01%	0.0
Wrap	3.879		
Cookie	2.673	67.04%	0.0
Roll	3.987		
Chips	2.610	62.97%	0.0
Banana	4.145		

There seems to be no clear bias evident between the observation lengths on either side of the screen. The image “Avocado-Cucumber” shows the greatest discrepancy between objects, although this may again be the result of software issues with split AOIs.

However, all the objects show clear evidence of statistical significance with all of the p-values approaching 0.

5.1.7 Time to First Fixation

Table 9: Results of analysis for left/right bias in Fixations Before, based on the mean values for each AOI.

	Mean	ratio l/r	p-value
Tomato	0.692	51.18%	0.0
Salami	1.353		
Avocado	0.682	50.57%	0.0
Cucumber	1.348		
Bacon	0.532	49.40%	0.0
Loin	1.076		
Grapes	0.510	49.40%	0.0
Candy	1.031		
Burger	0.752	93.55%	0.616504
Wrap	0.804		
Cookie	0.522	55.83%	0.00000113319
Roll	0.935		
Chips	0.610	62.99%	0.000301904
Banana	0.968		

The average Time to First Fixation is significantly lower for objects on the left side of the screen (approximately half of the TTFF for objects on the right side), reflecting a clear bias. Interestingly, the bias is least pronounced in the image “Burger-Wrap”, most likely due to the wrap’s close proximity to the center of the screen (while both AOIs have approximately the same area, the wrap’s oblong shape brings its left border closer to the center).

With the exception of Burger-Wrap, all p-values show a statistically significant distinction well above the 95% confidence level.

5.2 Distribution

The distribution of the data was evaluated using the single variable analysis function in Statgraphics. Due to the volume of the results, only the standardized skewness and standardized kurtosis are depicted here (the full results including the graphs can be found in the results file on the accompanying CD). If both values are between -2 and +2, the data can be assumed to follow a normal distribution.

5.2.1 First Fixation Duration

Table 10: Results of single variable analysis for the parameter First Fixation Duration. “Ratio” is the value of the high-caloric density AOI divided by that of the low-caloric density AOI.

Tomato-Salami	Tomato	Salami	Ratio
Stnd. skewness	14.7044	17.322	17.6251
Stnd. kurtosis	32.165	42.6812	48.2966

Avocado-Cucumber	Avocado	Cucumber	Ratio
Stnd. skewness	22.1732	7.73549	25.8695
Stnd. kurtosis	74.9567	7.2936	96.922

Bacon-Loin	Bacon	Lean loin	Ratio
Stnd. skewness	14.2119	13.7548	9.38165
Stnd. kurtosis	33.505	27.9623	10.758

Grapes-Candy	Grapes	Candy	Ratio
Stnd. skewness	20.3503	14.7926	14.2019
Stnd. kurtosis	59.4338	32.589	34.2171

Burger-Wrap	Cheeseburger	Chicken wrap	Ratio
Stnd. skewness	18.1969	10.3942	17.451
Stnd. kurtosis	57.0601	20.0303	47.3911

Cookie-Roll	Cookie	Pumpkinseed roll	Ratio
Stnd. skewness	11.6256	13.5106	28.281
Stnd. kurtosis	16.5371	22.444	114.044

Chips-Banana	Potato chips	Banana chips	Ratio
Stnd. skewness	18.8254	8.16846	10.2242
Stnd. kurtosis	49.4725	8.70449	11.2271

With all skewness and kurtosis ratings above +2, there is no evidence of a normal distribution. In general, the distributions are single-peaked, leptokurtic and have a positive skew.

5.2.2 Fixations Before

Table 11: Results of single variable analysis for the parameter Fixations Before. “Ratio” is the value of the high-caloric density AOI divided by that of the low-caloric density AOI.

Tomato-Salami	Tomato	Salami	Ratio
Stnd. skewness	12.2085	6.47653	6.36736
Stnd. kurtosis	16.3698	3.08767	3.45635

Avocado-Cucumber	Avocado	Cucumber	Ratio
Stnd. skewness	all values = 0	all values = 0	all values = 0
Stnd. kurtosis	all values = 0	all values = 0	all values = 0

Bacon-Loin	Bacon	Lean loin	Ratio
Stnd. skewness	24.9492	12.451	16.7118
Stnd. kurtosis	74.7331	18.5598	28.7313

Grapes-Candy	Grapes	Candy	Ratio
Stnd. skewness	16.2198	9.37691	8.31643
Stnd. kurtosis	28.2941	9.90342	9.23353

Burger-Wrap	Cheeseburger	Chicken wrap	Ratio
Stnd. skewness	21.1262	16.8023	18.8791
Stnd. kurtosis	50.0994	43.0208	44.7668

Cookie-Roll	Cookie	Pumpkinseed roll	Ratio
Stnd. skewness	25.2829	8.04287	13.5821
Stnd. kurtosis	77.9005	9.1372	24.7427

Chips-Banana	Potato chips	Banana chips	Ratio
Stnd. skewness	16.1443	14.4135	17.2497
Stnd. kurtosis	25.9415	28.8359	32.5788

With all skewness and kurtosis ratings above +2, there is no evidence of a normal distribution. Distributions are generally single-peaked, positively skewed and single-peaked.

Data from the image Avocado-Cucumber could not be analyzed since all values were returned by Tobii studio as “0”, presumably due to a problem with processing combined AOIs.

5.2.3 Fixation Count

Table 12: Results of single variable analysis for the parameter Fixation Count. “Ratio” is the value of the high-caloric density AOI divided by that of the low-caloric density AOI.

Tomato-Salami	Tomato	Salami	Ratio
Stnd. skewness	0.468674	1.82461	10.4102
Stnd. kurtosis	-0.705449	0.359451	15.294

Avocado-Cucumber	Avocado	Cucumber	Ratio
Stnd. skewness	0.998229	-0.864386	12.2817
Stnd. kurtosis	0.53698	-0.703509	23.3893

Bacon-Loin	Bacon	Lean loin	Ratio
Stnd. skewness	1.46998	1.08787	11.6828
Stnd. kurtosis	-1.29831	0.728535	21.5986

Grapes-Candy	Grapes	Candy	Ratio
Stnd. skewness	1.36284	1.56682	17.434
Stnd. kurtosis	-0.714291	-0.0978957	44.9572

Burger-Wrap	Cheeseburger	Chicken wrap	Ratio
Stnd. skewness	0.821254	1.2012	11.7197
Stnd. kurtosis	-0.831066	0.0766972	18.3157

Cookie-Roll	Cookie	Pumpkinseed roll	Ratio
Stnd. skewness	7.2583	-0.299904	18.158
Stnd. kurtosis	11.6919	-1.99327	41.508

Chips-Banana	Potato chips	Banana chips	Ratio
Stnd. skewness	1.66158	-0.328475	25.017
Stnd. kurtosis	0.442587	-0.731187	94.1461

With the exception of the cookie, all AOIs show skewness and kurtosis values between -2 and +2, indicating a normal distribution (the cookie being an exception presumably due to its small size). The values for the ratios far exceed the skewness and kurtosis expected from a normal distribution – while single-peaked, they show a strong positive skew and are highly leptokurtic.

5.2.4 Fixation Length

Table 13: Results of single variable analysis for the parameter Fixation Length. “Ratio” is the value of the high-caloric density AOI divided by that of the low-caloric density AOI.

Tomato-Salami	Tomato	Salami	Ratio
Stnd. skewness	-0.745536	0.463228	12.1334
Stnd. kurtosis	-0.709289	-1.00562	18.5239

Avocado-Cucumber	Avocado	Cucumber	Ratio
Stnd. skewness	-0.624675	-0.726298	31.6278
Stnd. kurtosis	-0.230109	0.0507893	130.39

Bacon-Loin	Bacon	Lean loin	Ratio
Stnd. skewness	0.101546	0.179893	15.4411
Stnd. kurtosis	-1.30388	0.944656	30.9258

Grapes-Candy	Grapes	Candy	Ratio
Stnd. skewness	-1.46465	-0.0320742	32.8639
Stnd. kurtosis	0.772131	-0.60116	144.572

Burger-Wrap	Cheeseburger	Chicken wrap	Ratio
Stnd. skewness	-0.00926155	-1.23469	10.8273
Stnd. kurtosis	-0.0972799	0.679924	17.4267

Cookie-Roll	Cookie	Pumpkinseed roll	Ratio
Stnd. skewness	1.69287	-2.00487	24.219
Stnd. kurtosis	0.645165	0.0153532	82.8157

Chips-Banana	Potato chips	Banana chips	Ratio
Stnd. skewness	1.88596	-2.46914	15.725
Stnd. kurtosis	0.801373	1.14502	30.2501

With the exception of the pumpkinseed roll and the banana chips with a skewness below -2, all AOIs show skewness and kurtosis values between -2 and +2, indicating a normal distribution. The values for the ratios far exceed the skewness and kurtosis expected from a normal distribution, being single peaked but having a strong positive skew and being highly leptokurtic.

5.2.5 Observation Count

Table 14: Results of single variable analysis for the parameter Observation Count. “Ratio” is the value of the high-caloric density AOI divided by that of the low-caloric density AOI.

Tomato-Salami	Tomato	Salami	Ratio
Stnd. skewness	4.4466	4.83061	12.7263
Stnd. kurtosis	4.7391	2.58235	33.8869

Avocado-Cucumber	Avocado	Cucumber	Ratio
Stnd. skewness	1.07538	-0.658044	10.4312
Stnd. kurtosis	0.512752	-0.7148	15.6021

Bacon-Loin	Bacon	Lean loin	Ratio
Stnd. skewness	0.394131	5.27629	8.63365
Stnd. kurtosis	-0.432789	4.62799	12.5185

Grapes-Candy	Grapes	Candy	Ratio
Stnd. skewness	2.22614	6.21422	9.9135
Stnd. kurtosis	0.114876	4.54853	13.904

Burger-Wrap	Cheeseburger	Chicken wrap	Ratio
Stnd. skewness	8.68079	17.2555	6.68541
Stnd. kurtosis	16.0145	55.6097	5.53277

Cookie-Roll	Cookie	Pumpkinseed roll	Ratio
Stnd. skewness	5.12629	8.21969	5.67487
Stnd. kurtosis	5.43137	13.2895	4.10405

Chips-Banana	Potato chips	Banana chips	Ratio
Stnd. skewness	1.42186	4.16179	8.46615
Stnd. kurtosis	-0.453276	1.52145	11.301

Some AOIs show both skewness and kurtosis values expected from a normal distribution, namely Avocado, Cucumber, Bacon and Potato Chips. The Grapes and Banana Chips fulfill the requirements for a kurtosis value of less than 2 while having a standardized skewness of more than two. The AOI Chicken wrap deviates strongly from the expected normal distribution. In general, distributions appear single-peaked in the density trace (the histogram is less useful here because the values are all integers and are spread out over a small range). The non-normally distributed values (which includes the ratios) are somewhat leptokurtic and have a positive skew.

5.2.6 Observation Length

Table 15: Results of single variable analysis for the parameter Observation Length. “Ratio” is the value of the high-caloric density AOI divided by that of the low-caloric density AOI.

Tomato-Salami	Tomato	Salami	Ratio
Stnd. skewness	-0.34892	0.498723	12.3617
Stnd. kurtosis	-0.749456	-0.896284	19.8767

Avocado-Cucumber	Avocado	Cucumber	Ratio
Stnd. skewness	2.38232	5.28806	16.5615
Stnd. kurtosis	0.186351	3.0245	41.5857

Bacon-Loin	Bacon	Lean loin	Ratio
Stnd. skewness	-0.00115422	-0.453063	15.5319
Stnd. kurtosis	-1.29213	0.0292043	31.6583

Grapes-Candy	Grapes	Candy	Ratio
Stnd. skewness	-1.42609	0.210853	38.607
Stnd. kurtosis	0.725466	-0.607904	187.327

Burger-Wrap	Cheeseburger	Chicken wrap	Ratio
Stnd. skewness	-0.0405449	-1.25181	10.9229
Stnd. kurtosis	-0.253216	0.889304	17.3333

Cookie-Roll	Cookie	Pumpkinseed roll	Ratio
Stnd. skewness	2.18185	-2.21443	30.5632
Stnd. kurtosis	1.40287	0.182779	126.785

Chips-Banana	Potato chips	Banana chips	Ratio
Stnd. skewness	1.77813	-2.59775	15.6388
Stnd. kurtosis	0.491899	1.37578	29.7358

9 out of 14 AOIs fall within the skewness and kurtosis range of +/-2 required for a normal distribution, while 3 fulfill the kurtosis requirement, but exceed the acceptable range for skewness. Only the AOI Cucumber shows both kurtosis and skewness values of above 2. On the other hand, none of the ratios demonstrate a normal distribution (instead being single-peaked, positive skewed and leptokurtic), with both Cookie-Roll and Grapes-Candy displaying a kurtosis value of over 100. Interestingly, the banana chips and pumpkinseed roll have negative skewness values below -2, making them platykurtic.

5.2.7 Time to First Fixation

Table 16: Results of single variable analysis for the parameter Time to First Fixation. “Ratio” is the value of the high-caloric density AOI divided by that of the low-caloric density AOI.

Tomato-Salami	Tomato	Salami	Ratio
Stnd. skewness	12.1306	6.54336	7.77301
Stnd. kurtosis	13.8307	2.56774	6.39882

Avocado-Cucumber	Avocado	Cucumber	Ratio
Stnd. skewness	10.5779	6.98657	12.2837
Stnd. kurtosis	10.0566	10.4406	15.3981

Bacon-Loin	Bacon	Lean loin	Ratio
Stnd. skewness	14.6397	11.3082	13.2962
Stnd. kurtosis	20.3775	13.0833	15.9744

Grapes-Candy	Grapes	Candy	Ratio
Stnd. skewness	20.9554	11.7975	13.3584
Stnd. kurtosis	53.2895	16.9033	25.2474

Burger-Wrap	Cheeseburger	Chicken wrap	Ratio
Stnd. skewness	16.2268	12.2139	12.9439
Stnd. kurtosis	29.0826	19.8271	19.0561

Cookie-Roll	Cookie	Pumpkinseed roll	Ratio
Stnd. skewness	18.6249	11.4364	26.2694
Stnd. kurtosis	42.4162	16.6443	102.503

Chips-Banana	Potato chips	Banana chips	Ratio
Stnd. skewness	18.5445	10.8926	16.9101
Stnd. kurtosis	40.2288	13.7751	31.8675

None of the AOIs or their ratios fulfills the prerequisites for a normal distribution, instead being highly leptokurtic and positively skewed.

5.3 Relation between BMI and Eye Tracking parameters

Using Statgraphics, a linear regression model was fitted to describe the relationships between BMI values (the independent variable) and the respective value for each AOI as well as the ratio of the value for the high-calorie AOI divided by that for the low-calorie AOI (the dependent variables). Additionally, a linear regression model was created to explain the relationship between the Median BMI values for each BMI group (<20, 20-25, 25-30, 30+) and the Median ratio. For the parameter Observation Count, an analysis of the Medians proved impossible in 3 out of 7 cases due to the values all being equal – since observation count values typically varied between 1 and 5, the Median ratio was deemed ill-suited to the task, so an analysis using the mean values was added.

The tables below show a summary of the data; the original tables and the accompanying graphs can be found in the results file on the CD.

5.3.1 BMI vs First Fixation Duration

Table 17: Results of simple linear regression for BMI vs First Fixation Duration. P-values below 0.05 are marked in green, P-values between 0.05 and 0.1 are marked in yellow. R²-values are marked in green if they exceed 50% (column "Medians BMI-ratio") or 2% (all other columns). R²-values between 20 and 50% (column "Medians BMI-ratio") or between 1-2% (all other columns) are marked in yellow.

Tomato-Salami	Medians BMI-ratio	BMI-ratio	BMI-Tomato	BMI-Salami
coefficient	-0.0878347	-0.0863404	-0.248535	0.275322
P-value	0.9380	0.9313	0.8040	0.7834
R-squared[%]	0.384264	0.00474797	0.0388338	0.0476517
Best model (R²[%])	Double Squared (0.98)	Double reciprocal (0.36)	Squared-Y logarithmic-X (0.39)	Square root-Y reciprocal-X (0.025)

Avocado-Cucumber	Medians BMI-ratio	BMI-ratio	BMI-Avocado	BMI-Cucumber
coefficient	0.406569	0.293927	0.31705	0.307811
P-value	0.7237	0.7692	0.7516	0.7586
R-squared[%]	7.63398	0.0549971	0.0631808	0.0595544
Best model (R²[%])	Double reciprocal (28.18)	Square root-Y reciprocal-X (0.16)	Square root-Y reciprocal-X (0.66)	Square root-Y logarithmic-X (0.27)

Bacon-Loin	Medians BMI-ratio	BMI-ratio	BMI-Bacon	BMI-Lean loin
coefficient	0.383877	0.263916	0.551835	0.809466
P-value	0.7380	0.7922	0.5818	0.4195
R-squared[%]	6.86244	0.0443444	0.191157	0.410406
Best model (R²[%])	Double reciprocal (28.71)	Squared-Y reciprocal-X (1.00)	Squared-Y reciprocal-X (1.33)	Square root-Y squared-X (1.07)

Grapes-Candy	Medians BMI-ratio	BMI-ratio	BMI-Grapes	BMI-Candy
coefficient	0.796214	-0.00391493	-0.974593	-0.182816
P-value	0.5094	0.9969	0.3312	0.8552
R-squared[%]	24.0686	0.00000963943	0.59383	0.0210155
Best model (R²[%])	Double squared (28.53)	Reciprocal-Y squared-X (0.73)	Square root-Y reciprocal-X (0.85)	Reciprocal-Y squared-X (0.17)

Burger-Wrap	Medians BMI-ratio	BMI-ratio	BMI-Burger	BMI-Wrap
coefficient	3.54107	1.50072	3.59603	1.31897
P-value	0.0713	0.1354	0.0004	0.1891
R-squared[%]	86.2441	1.41422	7.52129	1.08229
Best model (R²[%])	Double squared (90.42)	Squared-Y reciprocal-X (1.76)	Double squared (20.29)	Squared-X (1.24)

Cookie-Roll	Medians BMI-ratio	BMI-ratio	BMI-Cookie	BMI-Roll
coefficient	4.32845	1.10186	0.133845	-0.260439
P-value	0.0494	0.2722	0.8937	0.7949
R-squared[%]	90.3547	0.767373	0.0112658	0.0426413
Best model (R²[%])	Squared-Y logarithmic-X (92.51)	Squared-Y reciprocal-X (1.04)	Squared-X (0.08)	Double reciprocal (1.09)

Chips-Banana	Medians BMI-ratio	BMI-ratio	BMI-Chips	BMI-Banana
coefficient	1.07708	0.729707	1.69339	0.0449181
P-value	0.3941	0.4667	0.0923	0.9642
R-squared[%]	36.711	0.338008	1.77155	0.00126894
Best model (R²[%])	Double reciprocal (51.37	Double squared (0.91)	Double squared (10.67)	Squared-Y reciprocal-X (0.27)

The median ratios for the images "Burger-Wrap" and "Cookie-Roll" both produce R-squared values of 86.24 (at the 90% confidence level) and 90.35 ($P<0.05$) respectively.
By contrast, the models gained by fitting the complete set of values are significantly lower, with only Burger-Wrap producing an $R^2>1\%$ for all AOIs (particularly noteworthy is the AOI Burger, with an R^2 of 7.52 (20.29 using the Double Squared model) and a P-value of 0.0004.

In 3 out of the 7 images, the Squared Y-Reciprocal X model provides the highest R^2 value for the ratio vs BMI regression. For the Median ratios vs Median BMIs, the Double Reciprocal and Double Squared models are each preferable in 3 out of 7 cases.

5.3.2 BMI vs Fixations before

Table 18: Results of simple linear regression for BMI vs Fixations Before. P-values below 0.05 are marked in green, P-values between 0.05 and 0.1 are marked in yellow. R^2-values are marked in green if they exceed 50% (column “Medians BMI-ratio”) or 2% (all other columns). R^2-values between 20 and 50% (column “Medians BMI-ratio”) or between 1-2% (all other columns) are marked in yellow.

Tomato-Salami	Medians BMI-ratio	BMI-ratio	BMI-Tomato	BMI-Salami
coefficient	-1.88793	-0.369811	-0.211415	-0.503474
P-value	0.1996	0.7120	0.8328	0.6153
R-squared[%]	64.0565	0.0875898	0.0281031	0.159171
Best model (R^2[%])	S-curve model (74%)	Reciprocal-X (0.25)	Double squared (0.26)	Squared-Y reciprocal-X (0.38)

Avocado-Cucumber	Medians BMI-ratio	BMI-ratio	BMI-Avocado	BMI-Cucumber
coefficient	all values =0	all values =0	all values =0	all values =0
P-value	all values =0	all values =0	all values =0	all values =0
R-squared[%]	all values =0	all values =0	all values =0	all values =0
Best model (R^2[%])	all values =0	all values =0	all values =0	all values =0

Bacon-Loin	Medians BMI-ratio	BMI-ratio	BMI-Bacon	BMI-Lean loin
coefficient	1.02299	-0.489017	1.23538	0.385124
P-value	0.4139	0.6255	0.2185	0.7007
R-squared[%]	34.3511	0.150175	0.95072	0.0931962
Best model (R^2[%])	Squared-Y reciprocal-X (51.34)	Reciprocal-Y squared-X (0.24)	Squared-Y logarithmic-X (1.53)	Reciprocal-Y squared-X (1.10)

Grapes-Candy	Medians BMI-ratio	BMI-ratio	BMI-Grapes	BMI-Candy
coefficient	1.88793	1.26596	-0.727699	1.49633
P-value	0.1996	0.2074	0.4679	0.1365
R-squared[%]	64.0565	1.01048	0.331942	1.38863
Best model (R^2[%])	S-curve model(0.74)	Square root-Y squared-X (1.16)	Squared-X (0.50)	Reciprocal-X (1.63)

Burger-Wrap	Medians BMI-ratio	BMI-ratio	BMI-Burger	BMI-Wrap
coefficient	3.74851	1.72298	1.47974	-0.888263
P-value	0.0644	0.0869	0.1409	0.3757
R-squared[%]	87.54	1.85577	1.35841	0.493783
Best model (R^2[%])	Squared-X (92.45)	Squared-Y reciprocal-X (3.50)	Squared-Y reciprocal-X (2.31)	Square root-Y squared-X (0.64)

Cookie-Roll	Medians BMI-ratio	BMI-ratio	BMI-Cookie	BMI-Roll
coefficient	0.855289	0.8741	1.18582	-0.922757
P-value	0.4825	0.3834	0.2375	0.3575
R-squared[%]	26.7807	0.493688	0.876627	0.53267
Best model (R^2[%])	Squared-X (27.83)	Reciprocal-Y squared-X (1.03)	Squared-Y (0.95)	Square root-Y reciprocal-X (1.24)

Chips-Banana	Medians BMI-ratio	BMI-ratio	BMI-Chips	BMI-Banana
coefficient	-0.544117	2.44945	1.9357	-1.06542
P-value	0.6409	0.0154	0.0547	0.2883
R-squared[%]	12.8944	3.70359	2.3023	0.708852
Best model (R^2[%])	Square root-Y squared-X (16.89)	Square root-X (3.72)	Squared-Y logarithmic-X (2.93)	Reciprocal-Y (1.19)

The image “Burger-Wrap” again seems to yield promising results, with an R^2 of 87.54% and significance at the 90% confidence interval for the median ratios, and an R^2 of 1.86 (90% confidence level) for the individual values.

The image “Grapes-Candy” shows an R^2 value of 64.06, while not approaching statistical significance.

The image “Chips-Banana” is noteworthy in that while there does not seem to be a significant correlation between the medians, the ratio individual values shows a relatively strong correlation with an R^2 of 3.70 at the 95% confidence level. The potato chips themselves show an R^2 of 2.3, falling just short of the 95% confidence level (P=0.0547).

Interestingly, the “Fixations Before” function does not seem to work correctly with “split” AOIs (i.e. AOIs drawn separately and then given the same designation, so that the software recognizes them as a single AOI), yielding only 0-values.

5.3.3 BMI vs Fixation Count

Table 19: Results of simple linear regression for BMI vs Fixation Count. P-values below 0.05 are marked in green, P-values between 0.05 and 0.1 are marked in yellow. R^2-values are marked in green if they exceed 50% (column "Medians BMI-ratio") or 2% (all other columns). R^2-values between 20 and 50% (column "Medians BMI-ratio") or between 1-2% (all other columns) are marked in yellow.

Tomato-Salami	Medians BMI-ratio	BMI-ratio	BMI-Tomato	BMI-Salami
coefficient	1.38264	1.82877	-2.57352	-0.0390918
P-value	0.3009	0.0693	0.0110	0.9689
R-squared[%]	48.8713	2.08577	3.99884	0.000961103
Best model (R^2[%])	Squared-Y reciprocal-X (68.21)	Reciprocal-X (2.83)	Reciprocal-X (4.73)	Square root-Y squared-X (0.02)

Avocado-Cucumber	Medians BMI-ratio	BMI-ratio	BMI-Avocado	BMI-Cucumber
coefficient	-0.0870426	-1.13074	-3.03921	-1.9473
P-value	0.9386	0.2599	0.0028	0.0533
R-squared[%]	0.377391	0.807805	5.49034	2.32934
Best model (R^2[%])	Reciprocal-Y squared-X (2.34)	Reciprocal-Y squared-X (3.22)	Linear (5.49)	Squared-Y reciprocal-X (3.30)

Bacon-Loin	Medians BMI-ratio	BMI-ratio	BMI-Bacon	BMI-Lean loin
coefficient	-1.50716	-1.79802	-3.89369	-0.74478
P-value	0.2708	0.0741	0.0001	0.4575
R-squared[%]	53.1785	2.01761	8.70507	0.347654
Best model (R^2[%])	Reciprocal-Y squared-X (72.92)	Square root-Y logarithmic-X (2.52)	Logarithmic-X (9.03)	Logarithmic-Y squared-X (0.82)

Grapes-Candy	Medians BMI-ratio	BMI-ratio	BMI-Grapes	BMI-Candy
coefficient	0.0597789	1.58905	-2.86013	-0.41922
P-value	0.9578	0.1140	0.0048	0.6756
R-squared[%]	0.178357	1.56328	4.89313	0.11041
Best model (R^2[%])	Squared-Y reciprocal-X (2.12)	Exponential (2.13)	Linear (4.89)	Double reciprocal (0.28)

Burger-Wrap	Medians BMI-ratio	BMI-ratio	BMI-Burger	BMI-Wrap
coefficient	-2.46665	-0.393011	-2.15807	-1.75726
P-value	0.1325	0.6948	0.0324	0.0808
R-squared[%]	75.2609	0.0982838	2.84574	1.90511
Best model (R^2[%])	Reciprocal-Y squared-X (84.39)	Double reciprocal (0.40)	Square root-Y squared-X (4.22)	Square root-Y squared-X (2.51)

Cookie-Roll	Medians BMI-ratio	BMI-ratio	BMI-Cookie	BMI-Roll
coefficient	0.840991	0.740345	-0.698343	-2.66057
P-value	0.4889	0.4602	0.4860	0.0086
R-squared[%]	26.1247	0.3479	0.305781	4.26222
Best model (R^2[%])	Double squared (40.81)	Reciprocal-Y squared-X (1.10)	Square root-Y reciprocal-X (0.64)	Reciprocal-Y squared-X (6.70)

Chips-Banana	Medians BMI-ratio	BMI-ratio	BMI-Chips	BMI-Banana
coefficient	-1.84451	-0.0313658	-2.08665	-2.54222
P-value	0.2064	0.9750	0.0385	0.0120
R-squared[%]	62.9782	0.000626629	2.66543	3.90593
Best model (R^2[%])	Double reciprocal (80.72)	Squared-Y reciprocal-X (0.19)	Square root-Y squared-X (3.12)	Square root-Y squared-X (6.06)

The median ratios for Bacon-Loin, Burger-Wrap and Chips-Banana all produce R^2-values in excess of 50%, though none of them reach significance at even the 90% confidence level.

There are, however, significant interactions between several AOIs and the BMI value, at the 95% (tomato, burger, banana and potato chips) and in some cases the 99% confidence level (bacon, grapes and pumpkinseed roll), with relatively high R^2-values (up to 8.71%).

Interestingly, the coefficients for the individual AOIs are all negative – in other words, the number of fixations on the AOIs decreases with in people with higher BMIs. We also considered the possibility that the lower fixation count (meaning less eye movements) might be influenced by the higher average age of the obese group, since age correlates with a higher BMI).

The Reciprocal Y-Squared X model again provides the highest R^2 values for 3 out of 7 cases for the Median ratios vs Median BMIs, as well as 2 out of 7 cases for the ratios vs BMIs. For the individual AOIs, the Square root Y-Squared X yields the highest R^2-values in 5 out of 12 cases.

5.3.4 BMI vs Fixation Length

Table 20: Results of simple linear regression for BMI vs Fixation Length. P-values below 0.05 are marked in green, P-values between 0.05 and 0.1 are marked in yellow. R^2-values are marked in green if they exceed 50% (column "Medians BMI-ratio") or 2% (all other columns). R^2-values between 20 and 50% (column "Medians BMI-ratio") or between 1-2% (all other columns) are marked in yellow.

Tomato-Salami	Medians BMI-ratio	BMI-ratio	BMI-Tomato	BMI-Salami
coefficient	0.701988	2.2317	-2.91766	1.26946
P-value	0.5554	0.0271	0.0040	0.2061
R-squared[%]	19.7685	3.07474	5.08185	1.00336
Best model (R²[%])	Double reciprocal (40.80)	Square root-Y logarithmic-X (3.24)	Logarithmic-X (5.31)	Double squared (1.56)

Avocado-Cucumber	Medians BMI-ratio	BMI-ratio	BMI-Avocado	BMI-Cucumber
coefficient	-0.229671	-1.79304	-3.49055	0.0455402
P-value	0.8397	0.0749	0.0006	0.9637
R-squared[%]	2.56966	2.00668	7.11744	0.00130433
Best model (R²[%])	Reciprocal-Y squared-X (5.76)	Reciprocal-Y squared-X (4.62)	Linear (7.12	Square root-Y squared-X (0.13)

Bacon-Loin	Medians BMI-ratio	BMI-ratio	BMI-Bacon	BMI-Lean loin
coefficient	-0.89087	-1.90361	-3.15479	-0.0783263
P-value	0.4670	0.0588	0.0019	0.9377
R-squared[%]	28.409	2.25604	5.89081	0.00385835
Best model (R²[%])	Reciprocal-Y squared-X (54.81)	Square root-Y (2.61)	Square root-Y logarithmic-X (6.35)	S-curve model (0.03)

Grapes-Candy	Medians BMI-ratio	BMI-ratio	BMI-Grapes	BMI-Candy
coefficient	0.722299	2.10858	-2.27051	1.70534
P-value	0.5451	0.0365	0.0245	0.0901
R-squared[%]	20.6889	2.72024	3.14044	1.7962
Best model (R²[%])	Double squared (29.06)	Square root-Y reciprocal-X (4.29)	Square root-Y reciprocal-X (3.45)	Squared-Y (2.43)

Burger-Wrap	Medians BMI-ratio	BMI-ratio	BMI-Burger	BMI-Wrap
coefficient	-0.172685	0.249995	-0.863808	-1.14951
P-value	0.8788	0.8029	0.3890	0.2521
R-squared[%]	1.4691	0.0397915	0.467094	0.824209
Best model (R²[%])	Reciprocal-Y squared-X (3.98)	Squared-Y reciprocal-X (0.81)	Square root-Y reciprocal-X (1.03)	Square root-Y reciprocal-X (2.25)

Cookie-Roll	Medians BMI-ratio	BMI-ratio	BMI-Cookie	BMI-Roll
coefficient	4.07026	0.560814	1.05357	-2.65867
P-value	0.0554	0.5757	0.2937	0.0086
R-squared[%]	89.2282	0.199926	0.693281	4.25638
Best model (R²[%])	Reciprocal-Y squared-X (94.15)	Reciprocal-Y square root-X (2.11)	Squared-Y reciprocal-X (1.07)	Squared-Y square root-X (4.37)

Chips-Banana	Medians BMI-ratio	BMI-ratio	BMI-Chips	BMI-Banana
coefficient	-2.36005	-0.740906	-1.36911	-0.595399
P-value	0.1422	0.4599	0.1729	0.5524
R-squared[%]	73.5793	0.348426	1.16517	0.22246
Best model (R^2[%])	Reciprocal-Y squared-X (82.92)	Square root-Y logarithmic-X (0.41)	Squared-Y (1.18)	Square root-Y (0.68)

For the median ratios, Cookie-Roll and Chips-Banana yield relatively high R^2-values of 89.23% and 73.58%, respectively, with the former displaying statistical significance approaching the 95% confidence interval.

For the complete ratio values, there is a significant interaction at the 95% confidence interval in the Tomato-Salami and Grapes-Candy images.

The AOIs tomato, avocado, bacon, grapes and pumpkinseed roll all show a significant interaction at the 95% confidence interval or above. Interestingly, the total Fixation Length on these AOIs is negatively correlated with a higher BMI.

For 5 out of 7 images, the Reciprocal Y-Squared X model provides the best results for the Median ratios vs Median BMI values.

5.3.5 BMI vs Observation Count

Table 21: Results of simple linear regression for BMI vs Observation Count. P-values below 0.05 are marked in green, P-values between 0.05 and 0.1 are marked in yellow. R^2-values are marked in green if they exceed 50% (column "Medians BMI-ratio" and "Means BMI-ratio) or 2% (all other columns). R^2-values between 20 and 50% (column "Medians BMI-ratio") or between 1-2% (all other columns) are marked in yellow.

Tomato-Salami	Medians BMI-ratio	Means BMI-ratio	BMI-ratio	BMI-Tomato	BMI-Salami
coefficient	1.02299	0.935621	-0.19114	1.39659	1.23677
P-value	0.4139	0.4482	0.8487	0.1645	0.2180
R-squared[%]	34.3511	30.4441	0.023265	1.21184	0.952853
Best model (R²[%])	Squared-Y reciprocal-X (51.34)	Double reciprocal (43.81)	Double reciprocal (0.14)	Squared-Y square root-X (1.55)	Squared-Y reciprocal-X (2.27)

Avocado-Cucumber	Medians BMI-ratio	Means BMI-ratio	BMI-ratio	BMI-Avocado	BMI-Cucumber
coefficient	-0.144151	-0.577836	-1.35599	-3.3192	-2.1589
P-value	0.8986	0.6218	0.1771	0.0011	0.0324
R-squared[%]	1.02828	14.3063	1.15759	6.47998	2.84788
Best model (R²[%])	Reciprocal-Y squared-X (4.47)	Reciprocal-Y squared-X (20.61)	Reciprocal-Y squared-X (2.58)	Linear (6.48)	Squared-Y logarithmic-X (3.99)

Bacon-Loin	Medians BMI-ratio	Means BMI-ratio	BMI-ratio	BMI-Bacon	BMI-Lean loin
coefficient	-0.0162082	-1.72827	-1.49638	-1.14014	1.45849
P-value	0.9885	0.2261	0.1366	0.2559	0.1467
R-squared[%]	0.0131336	59.8951	1.40615	0.810928	1.32019
Best model (R²[%])	Squared-Y reciprocal-X (2.05)	Reciprocal-Y squared-X (72.49)	S-curve model (1.93)	Square root-Y reciprocal-X (2.13)	Squared-Y logarithmic-X (2.61

Grapes-Candy	Medians BMI-ratio	Means BMI-ratio	BMI-ratio	BMI-Grapes	BMI-Candy
coefficient	1.02299	1.39914	0.504972	0.30564	0.792096
P-value	0.4139	0.2967	0.6143	0.7603	0.4295
R-squared[%]	34.3511	49.4644	0.160118	0.0587178	0.39305
Best model (R²[%])	Double reciprocal (51.34)	Logistic (80.55)	Square root-Y reciprocal-X (0.54)	Squared-Y (0.36)	Squared-Y reciprocal-X (1.05)

Burger-Wrap	Medians BMI-ratio	Means BMI-ratio	BMI-ratio	BMI-Burger	BMI-Wrap
coefficient	values are all equal	-0.446076	-0.111838	0.00682966	0.072346
P-value	values are all equal	0.6992	0.9111	0.9946	0.9424
R-squared[%]	values are all equal	9.04891	0.00796601	0.000029336	0.00329168
Best model (R²[%])	values are all equal	Reciprocal-Y squared-X (17.35)	Reciprocal-Y squared-X (0.04)	Squared-Y square root-X (1.11)	Squared-Y logarithmic-X (0.83)

Cookie-Roll	Medians BMI-ratio	Means BMI-ratio	BMI-ratio	BMI-Cookie	BMI-Roll
coefficient	values are all equal	-0.658178	-0.157704	-0.322142	0.332
P-value	values are all equal	0.5781	0.8749	0.7478	0.7403
R-squared[%]	values are all equal	17.8037	0.0158386	0.065225	0.0692753
Best model (R^2[%])	values are all equal	Reciprocal-Y squared-X (21.85)	Double squared (0.09)	Square root-Y squared-X (0.41)	Double reciprocal (2.07)

Chips-Banana	Medians BMI-ratio	Means BMI-ratio	BMI-ratio	BMI-Chips	BMI-Banana
coefficient	values are all equal	-2.30407	-0.238833	-0.879115	-1.17886
P-value	values are all equal	0.1477	0.8115	0.3807	0.2402
R-squared[%]	values are all equal	72.6355	0.0363189	0.483714	0.866455
Best model (R^2[%])	values are all equal	Reciprocal-Y squared-X (79.75)	Squared-Y reciprocal-X (0.22)	Square root-Y squared-X (1.38)	Square root-Y squared-X (2.20)

Due to the low number of Observations (typically between 1 and 5 per AOI), the Median values did not allow for a meaningful analysis when using the median values; consequently, we also performed a simple regression analysis for the mean values. In both cases, no statistically significant correlations were found, however. The Reciprocal Y-Squared X model yielded the highest R^2 values in 5 out of 7 cases for the Mean ratio vs Mean BMI analysis.

The only instance of statistically significant interaction at the 95% confidence level is with the image “Avocado-Cucumber”, where the two AOIs display p-values of 0.0011 and 0.0324 and R^2-values of 6.48 and 2.85, respectively.

5.3.6 BMI vs Observation Length

Table 22: Results of simple linear regression for BMI vs Observation Length. P-values below 0.05 are marked in green, P-values between 0.05 and 0.1 are marked in yellow. R^2-values are marked in green if they exceed 50% (column "Medians BMI-ratio") or 2% (all other columns). R^2-values between 20 and 50% (column "Medians BMI-ratio") or between 1-2% (all other columns) are marked in yellow.

Tomato-Salami	Medians BMI-ratio	BMI-ratio	BMI-Tomato	BMI-Salami
coefficient	1.065	2.12156	-2.76224	1.29441
P-value	0.3984	0.0354	0.0064	0.1974
R-squared[%]	36.1882	2.78699	4.57899	1.04279
Best model (R²[%])	Double reciprocal (57.62)	Square root-Y logarithmic-X (3.00)	Reciprocal-X (4.84)	Double squared (1.64)

Avocado-Cucumber	Medians BMI-ratio	BMI-ratio	BMI-Avocado	BMI-Cucumber
coefficient	-0.0446529	-0.60878	-3.30823	-1.46459
P-value	0.9684	0.5438	0.0012	0.1450
R-squared[%]	0.0995947	0.290973	6.43996	1.33111
Best model (R²[%])	Squared-Y reciprocal-X (1.73)	Reciprocal-Y squared-X (3.83)	Linear (6.44)	Square root-Y reciprocal-X (2.14)

Bacon-Loin	Medians BMI-ratio	BMI-ratio	BMI-Bacon	BMI-Lean loin
coefficient	-1.12019	-1.91156	-3.10235	0.327819
P-value	0.3791	0.0578	0.0023	0.7435
R-squared[%]	38.5528	2.27449	5.70769	0.0675425
Best model (R²[%])	Reciprocal-Y squared-X (61.94)	Square root-Y (2.65)	Square root-Y logarithmic-X (6.28)	Squared-Y (0.12)

Grapes-Candy	Medians BMI-ratio	BMI-ratio	BMI-Grapes	BMI-Candy
coefficient	0.370527	1.87154	-2.18376	1.51296
P-value	0.7466	0.0631	0.0304	0.1323
R-squared[%]	6.42358	2.15544	2.91191	1.41921
Best model (R²[%])	Double squared (12.38)	Square root-Y reciprocal-X (3.81)	S-curve model (3.35)	Squared-Y (1.80)

Burger-Wrap	Medians BMI-ratio	BMI-ratio	BMI-Burger	BMI-Wrap
coefficient	-0.150166	0.262741	-0.917551	-1.2377
P-value	0.8944	0.7931	0.3602	0.2177
R-squared[%]	1.11492	0.0439507	0.526708	0.954273
Best model (R²[%])	Reciprocal-Y squared-X (2.75)	Squared-Y reciprocal-X (0.77)	Square root-Y reciprocal-X (1.07)	Square root-Y reciprocal-X (2.39)

Cookie-Roll	Medians BMI-ratio	BMI-ratio	BMI-Cookie	BMI-Roll
coefficient	2.49442	0.380387	1.0229	-2.54966
P-value	0.1301	0.7042	0.3079	0.0117
R-squared[%]	75.6754	0.0920772	0.653762	3.92794
Best model (R²[%])	Double squared (83.74)	Reciprocal-Y square root-X (2.13)	Squared-Y reciprocal-X (0.75)	Squared-Y square root-X (4.03)

Chips-Banana	Medians BMI-ratio	BMI-ratio	BMI-Chips	BMI-Banana
coefficient	-3.231	-0.673595	-1.15114	-0.417848
P-value	0.0839	0.5016	0.2514	0.6766
R-squared[%]	83.922	0.288168	0.826518	0.109689
Best model (R^2[%])	Reciprocal-Y squared-X (89.62)	Square root-Y reciprocal-X	Square root-Y logarithmic-X (0.88)	Square root-Y squared-X (0.44)

There is a statistically significant interaction at the 95% confidence level between ratio and BMI for the image Tomato-Salami, and at the 90% confidence level for the images Bacon-Loin and Grapes Candy. There is also a statistically significant interaction at the 99% confidence level for the AOIs Tomato, Avocado and Bacon and at the 95% level for the AOIs Grapes and Roll, with R-squared values of up to 6.44.

In the image Chips-Banana, the Median BMI explains 83.92% of the variability in Median Ratio at a 90% confidence level. In 3 out of 7 cases, the relationship between Median ratio and Median BMI is best explained by the Reciprocal Y-Squared X model.

5.3.7 BMI vs Time to First Fixation

Table 23: Results of simple linear regression for BMI vs Time to First Fixation. P-values below 0.05 are marked in green, P-values between 0.05 and 0.1 are marked in yellow. R^2-values are marked in green if they exceed 50% (column "Medians BMI-ratio") or 2% (all other columns). R^2-values between 20 and 50% (column "Medians BMI-ratio") or between 1-2% (all other columns) are marked in yellow.

Tomato-Salami	Medians BMI-ratio	BMI-ratio	BMI-Tomato	BMI-Salami
coefficient	-5.87535	0.243613	-0.357009	-0.207203
P-value	0.0278	0.8079	0.7216	0.8361
R-squared[%]	94.5235	0.0380285	0.0806028	0.0271654
Best model (R^2[%])	Reciprocal-Y (98.61)	Double squared (1.00)	Double reciprocal (0.97)	Squared-Y reciprocal-X (0.25)

Avocado-Cucumber	Medians BMI-ratio	BMI-ratio	BMI-Avocado	BMI-Cucumber
coefficient	2.40106	-0.563325	0.4915	-0.0813739
P-value	0.1384	0.5740	0.6238	0.9352
R-squared[%]	74.2436	0.201716	0.153631	0.00421748
Best model (R^2[%])	Squared-Y reciprocal-X (92.03)	Double reciprocal (1.59)	Double reciprocal (3.36)	Squared-Y reciprocal-X (0.34)

Bacon-Loin	Medians BMI-ratio	BMI-ratio	BMI-Bacon	BMI-Lean loin
coefficient	0.189793	-1.13214	-0.621954	1.34106
P-value	0.8670	0.2593	0.5349	0.1818
R-squared[%]	1.76921	0.809788	0.245781	1.11845
Best model (R^2[%])	Double squared (3.70)	Squared-X (0.81)	Reciprocal-X (0.33)	Logarithmic-Y squared-X (1.58)

Grapes-Candy	Medians BMI-ratio	BMI-ratio	BMI-Grapes	BMI-Candy
coefficient	-0.106412	1.30273	-1.19083	1.45321
P-value	0.9250	0.1946	0.2355	0.1481
R-squared[%]	0.562984	1.06271	0.883987	1.31079
Best model (R^2[%])	Reciprocal-Y squared-X (2.70)	Double squared (1.73)	Squared-X (0.92)	Double squared (1.86)

Burger-Wrap	Medians BMI-ratio	BMI-ratio	BMI-Burger	BMI-Wrap
coefficient	0.429528	0.578911	0.851975	0.109941
P-value	0.7094	0.5635	0.3955	0.9126
R-squared[%]	8.44563	0.215751	0.460205	0.0076495
Best model (R^2[%])	Double squared (15.55)	Squared-Y reciprocal-X (0.58)	Squared-Y reciprocal-X (0.98)	Double reciprocal (0.23)

Cookie-Roll	Medians BMI-ratio	BMI-ratio	BMI-Cookie	BMI-Roll
coefficient	0.413298	0.496535	0.47193	0.707206
P-value	0.7195	0.6202	0.6376	0.4805
R-squared[%]	7.86872	0.160883	0.141657	0.313568
Best model (R^2[%])	Double squared (12.32)	Squared-Y reciprocal-X (0.56)	Square root-Y squared-X (0.47)	Double squared (0.91)

Chips-Banana	Medians BMI-ratio	BMI-ratio	BMI-Chips	BMI-Banana
coefficient	1.19406	2.47428	2.77409	-0.16666
P-value	0.3549	0.0144	0.0062	0.8679
R-squared[%]	41.619	3.75305	4.67261	0.0175765
Best model (R^2[%])	Squared-Y reciprocal-X (59.65)	Squared-Y reciprocal-X (4.90)	Reciprocal-X (5.75)	Squared-Y reciprocal-X (0.18)

In the image Tomato-Salami, the regression model of Median ratio vs Median BMI explains 94.52% of the variability in that variable, with a 95% confidence level.

Other than that, the only the image Chips-Banana contains a statistically significant interaction for the ratio (P-value = 0.0144, R^2 = 3.75) and the AOI Chips (P-value 0.0062, R^2 = 4.67).

Again, the Squared Y-Reciprocal X model provides the highest R-squared values for ratio vs BMI in 3 out of 7 images.

5.3.8 Age vs Fixation Count

Table 24: Results of simple linear regression for the parameters Age vs Fixation count. P-values below 0.05 are marked in green; P-values between 0.05 and 0.1 are marked in yellow. R^2-values are marked in green if they exceed 2%, and yellow if they fall between 1-2%.

Tomato-Salami	Age-Tomato	Age-Salami
coefficient	-2.75542	1.01248
P-value	0.0065	0.3128
R-squared[%]	4.55744	0.640599
Best model (R^2[%])	Squared-X (5.27)	Logarithmic-X (0.72)

Avocado-Cucumber	Age-Avocado	Age-Cucumber
coefficient	-2.19002	-1.22728
P-value	0.0300	0.2215
R-squared[%]	2.92815	0.938421
Best model (R^2[%])	Squared-X (3.29)	Linear (0.94)

Bacon-Loin	Age-Bacon	Age-Lean loin
coefficient	-2.93232	-0.690621
P-value	0.0039	0.4908
R-squared[%]	5.13043	0.299076
Best model (R^2[%])	Square root-Y squared-X (6.77)	Logarithmic-Y squared-X (0.65)

Grapes-Candy	Age-Grapes	Age-Candy
coefficient	-2.59373	1.70852
P-value	0.0104	0.0895
R-squared[%]	4.05935	1.80279
Best model (R^2[%])	Logarithmic-Y squared-X (6.56)	Double reciprocal (3.16)

Burger-Wrap	Age-Burger	Age-Wrap
coefficient	-3.05259	-0.785723
P-value	0.0027	0.4332
R-squared[%]	5.53612	0.386775
Best model (R^2[%])	Square root-Y squared-X (8.82)	Square root-Y squared-X (1.42)

Cookie-Roll	Age-Cookie	Age-Roll
coefficient	0.72638	-0.930747
P-value	0.4687	0.3534
R-squared[%]	0.330744	0.541884
Best model (R^2[%])	Square root-Y logarithmic-X (0.59)	Double squared (0.84)

Chips-Banana	Age-Chips	Age-Banana
coefficient	-0.777293	-1.66562
P-value	0.4381	0.0978
R-squared[%]	0.378552	1.71491
Best model (R^2[%])	Squared-X (0.57)	Square root-Y reciprocal-X (2.18)

In 5 out of 7 images, there is a statistically significant correlation between age and the fixation count for an AOI at the 95% confidence level or above. In all of these, the correlation is negative, meaning that older participants generally have a lower number of fixations on these eyes. Interestingly enough, this only applies to objects on the left side of the screen. On the right side, there are no significant interactions on the 95% confidence level, although there are two with significance at the 90% confidence interval. Interestingly enough, the correlation is positive for the relationship between Age and Candy, while the opposite holds true for Age and Banana.

5.3.9 Age vs Fixation Length

Table 25: Results of simple linear regression for the parameters Age vs Fixation length. P-values below 0.05 are marked in green; P-values between 0.05 and 0.1 are marked in yellow. R^2-values are marked in green if they exceed 2%, and yellow if they fall between 1-2%.

Tomato-Salami	Age-Tomato	Age-Salami
coefficient	-3.28395	0.258155
P-value	0.0013	0.7966
R-squared[%]	6.35176	0.0418968
Best model (R^2[%])	Squared-X (7.38)	Square root-Y logarithmic-X (0.09)

Avocado-Cucumber	Age-Avocado	Age-Cucumber
coefficient	-3.05439	-1.33549
P-value	0.0026	0.1836
R-squared[%]	5.54228	1.10927
Best model (R^2[%])	Squared-X (6.40)	Reciprocal-X (1.27)

Bacon-Loin	Age-Bacon	Age-Lean loin
coefficient	-2.50971	-0.796099
P-value	0.0131	0.4272
R-squared[%]	3.81046	0.397018
Best model (R^2[%])	Square root-Y squared-X (5.99)	Logarithmic-Y squared-X (0.82)

Grapes-Candy	Age-Grapes	Age-Candy
coefficient	-3.42375	2.13803
P-value	0.0008	0.0340
R-squared[%]	6.86617	2.7946
Best model (R^2[%])	Logarithmic-Y squared-X (9.71)	Double reciprocal (4.19)

Burger-Wrap	Age-Burger	Age-Wrap
coefficient	-2.51283	-1.66933
P-value	0.0130	0.0970
R-squared[%]	3.81958	1.72242
Best model (R^2[%])	Square root-Y squared-X (6.83)	Square root-Y squared-X (4.49)

Cookie-Roll	Age-Cookie	Age-Roll
coefficient	0.489374	-1.62565
P-value	0.6253	0.1060
R-squared[%]	0.150394	1.63492
Best model (R^2[%])	Square root-Y (0.24)	Double squared (2.72)

Chips-Banana	Age-Chips	Age-Banana
coefficient	-1.79752	-1.1277
P-value	0.0742	0.2611
R-squared[%]	1.99165	0.793463
Best model (R^2[%])	Squared-X (2.44)	Square root-Y squared-X (1.21)

In 5 out of 7 images, there is a statistically significant correlation between age and the fixation count for an AOI at the 95% confidence level or above. In all of these, the Fixation Length on the left-side AOI is negatively correlated with age (additionally, the AOI Chips displays a negative correlation with Age at a 90% confidence level). On the other hand, no such clear relationship exists for the right-hand objects – Candy displays a positive correlation with Age on the 95% confidence level, while Wrap displays a negative correlation on the 90% confidence level.

5.4 Multiple Variable Analysis

Multiple Variable Analysis is a relatively new feature in Statgraphics, designed to summarize multiple columns of data and calculate correlations and covariances between them. While it is not as intuitively interpretable and “compact” as a graphical Principal Component Analysis biplot, it provides a more scientifically sound (i.e. not dependent on the individual interpretation of a human analyst) method of exploring statistical interactions, especially in models involving a large number of variables, as is the case here.

For the purpose of this thesis, we were looking for correlations between the two AOIs as well as between the AOIs and the various demographic variables. To yield more accurate results, “ratio” (the ratio between the two values for the two AOIs, as calculated in Excel) was used as the selection variable (so that only rows with a positive, non-zero value for both AOIs would be considered).

Due to the large size of the tables produced by this function, they can be found in the results files on the accompanying CD.

The variables demonstrating a strong statistical correlation (95% confidence level and above) with the respective AOIs were then used to formulate a Multiple Regression model (see below),

5.5 Multiple Regression Analysis

After a significant interaction (95% confidence level or higher) between AOIs and demographic variables was confirmed in the Multiple Variable Analysis, a multiple linear regression model was created based on these factors, again using Statgraphics.

5.5.1 Demographic Factors

BMI

Dependent variable: BMI
Independent variables:
inc_meds
metabolic
mood
satiety
age

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	49,7673	4,85972	10,2408	0,0000
inc_meds	-11,6119	1,72241	-6,74165	0,0000
metabolic	4,59216	2,02281	2,27019	0,0246
mood	-3,44955	1,52879	-2,2564	0,0254
satiety	-0,891703	0,860104	-1,03674	0,3015
age	0,228451	0,05396	4,23372	0,0000

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	6949,61	5	1389,92	30,55	0,0000
Residual	7051,87	155	45,496		
Total (Corr.)	14001,5	160			

R-squared = 49,6348 percent

A model comprised of inc_meds, metabolic, mood, satiety and age explains 49.63% of the variability in BMI. In particular, people with higher BMIs are more likely to be older and to be taking appetite-increasing medication (with a statistical significance above the 99% confidence level). At the 95% confidence level, there is also a correlation between mood (a higher BMI is associated with agitation) and the presence of a metabolic disorder (more common in those with higher BMIs).

Gender

Multiple Regression - gender

Dependent variable: gender
Independent variables:
habits
carbs
prot_lip

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	1,22481	0,156803	7,8111	0,0000
habits	0,140522	0,075922	1,85087	0,0661
carbs	-0,182316	0,0887687	-2,05383	0,0417
prot_lip	0,184697	0,0852241	2,16719	0,0317

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	3,7628	3	1,25427	5,52	0,0012
Residual	35,6658	157	0,227171		
Total (Corr.)	39,4286	160			

R-squared = 9,54333 percent

A model comprised of habits, carbs and prot_lip explains 9.54% of the variability in gender. Males are therefore more likely to take in their food in fewer but larger meals and show a preference for proteins and fats over carbohydrates.

5.5.2 First Fixation Duration

Tomato-Salami

Dependent variable: Salami
Independent variables:
A.dec_meds
A.carbs
Selection variable: A.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	0.680238	0.105784	6.43045	0.0000
A.dec_meds	-0.150797	0.0533963	-2.82411	0.0054
A.carbs	-0.0659517	0.0349732	-1.88578	0.0612

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	0.4768	2	0.2384	6.64	0.0017
Residual	5.60052	156	0.0359007		
Total (Corr.)	6.07731	158			

R-squared = 7.84557 percent

A model comprised of dec_meds and carbs explains 7.85% of the variability in Salami, with dec_meds showing a significant relationship at the 95% confidence level, meaning that people not taking appetite-decreasing medication have a decreased duration of the first fixation on the AOI salami.

Avocado-Cucumber

Dependent variable: Avocado
Independent variables:
B.allergy
Selection variable: B.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	0.468957	0.0854692	5.48686	0.0000
B.allergy	-0.0940426	0.0447887	-2.09969	0.0374

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	0.147956	1	0.147956	4.41	0.0374
Residual	5.26892	157	0.03356		
Total (Corr.)	5.41688	158			

R-squared = 2.7314 percent

Allergy explains 2.73% of the variability in Avocado, meaning people without allergies have a shorter duration of first fixation.

Bacon-Loin

Dependent variable: Loin
Independent variables:
C.gender
Selection variable: C.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	0.479378	0.0498199	9.62222	0.0000
C.gender	-0.0684374	0.0329722	-2.07561	0.0396

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	0.182281	1	0.182281	4.31	0.0396
Residual	6.64276	157	0.0423106		
Total (Corr.)	6.82504	158			

R-squared = 2.67076 percent

A model based on gender explains 2.67% of the variability in Loin, meaning male participants have a shorter first fixation duration on the lean loin.

Grapes-Candy

Dependent variable: Grapes
Independent variables:
D.gender
D.prot_lip
Selection variable: D.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	0.585614	0.0638904	9.16592	0.0000
D.gender	-0.0990868	0.0411763	-2.40641	0.0173
D.prot_lip	-0.0670144	0.0451063	-1.4857	0.1394

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	0.637126	2	0.318563	4.99	0.0079
Residual	10.0772	158	0.0637797		
Total (Corr.)	10.7143	160			

R-squared = 5.94649 percent

A model comprised of gender and prot_lip explains 5.95% of the variability in Grapes, with gender showing a statistically significant relationship at the 95% confidence level, meaning male participants tend to have a shorter duration of first fixation on the grapes.

Dependent variable: Candy
Independent variables:
D.prot_lip
Selection variable: D.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	0.530498	0.038315	13.8457	0.0000
D.prot_lip	-0.10017	0.0453349	-2.20955	0.0286

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	0.329688	1	0.329688	4.88	0.0286
Residual	10.7372	159	0.0675298		
Total (Corr.)	11.0669	160			

R-squared = 2.97904 percent

A model based on prot_lip explains 2.98% of the variability in Candy with a statistically significant relationship at the 95% confidence level, meaning that a preference for proteins and lipids is related to a shorter duration of first fixation on the candy.

Burger-Wrap

Dependent variable: Burger
Independent variables:
E.inc_meds
E.BMI
Selection variable: E.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	0.179994	0.14751	1.22021	0.2242
E.inc_meds	-0.00172822	0.0573159	-0.0301524	0.9760
E.BMI	0.00688425	0.00204039	3.37399	0.0009

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	0.649121	2	0.324561	8.46	0.0003
Residual	5.98623	156	0.0383732		
Total (Corr.)	6.63535	158			

R-squared = 9.78278 percent

A model comprised of inc_meds and BMI explains 9.78% of the variability in Burger, with BMI showing a statistical relationship at the 95% confidence level, suggesting that people with higher BMIs tend to have a longer first fixation on the cheeseburger.

Cookie-Roll

Dependent variable: Burger
Independent variables:
E.inc_meds
E.BMI
Selection variable: E.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	0.179994	0.14751	1.22021	0.2242
E.inc_meds	-0.00172822	0.0573159	-0.0301524	0.9760
E.BMI	0.00688425	0.00204039	3.37399	0.0009

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	0.649121	2	0.324561	8.46	0.0003
Residual	5.98623	156	0.0383732		
Total (Corr.)	6.63535	158			

R-squared = 9.78278 percent

A model comprised of allergy and Cookie explains 7.63% of the variability in Roll, with allergy showing statistical significance on the 95% confidence level, meaning that people without allergies tend to have a shorter duration of first fixation on the pumpkin seed roll.

Chips-Banana

Dependent variable: Chips
Independent variables:
G.allergy
Selection variable: G.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	0.574523	0.111311	5.1614	0.0000
G.allergy	-0.115479	0.058331	-1.97972	0.0495

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	0.223095	1	0.223095	3.92	0.0495
Residual	8.93681	157	0.0569223		
Total (Corr.)	9.1599	158			

R-squared = 2.43556 percent

There is evidence of a statistically significant (95% confidence level) relationship between Chips and allergy, explaining 2.44% of the variability in Chips (people without allergies tend to have a shorter first fixation duration on the potato chips).

5.5.3 Fixations before

Tomato-Salami

Dependent variable: Tomato
Independent variables:
  Salami
  A.satiety
Selection variable: A.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	4.41923	0.488513	9.04628	0.0000
Salami	-0.237719	0.0440242	-5.39973	0.0000
A.satiety	-0.596083	0.233879	-2.54868	0.0118

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	123.705	2	61.8525	17.35	0.0000
Residual	552.472	155	3.56434		
Total (Corr.)	676.177	157			

R-squared = 18.2948 percent

A model comprised of Salami and satiety explains 18.29% of the variability in Tomato, meaning a hungry person will have a lower number of fixations before first fixating on the tomato.

Avocado-Cucumber

All values for “Fixations Before” for Avocado-Cucumber equal 0, possibly due to the image being the only with “split” AOIs.

Bacon-Loin

Dependent variable: Bacon
Independent variables:
  C.metabolic
Selection variable: C.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	1.9021	0.234868	8.09858	0.0000
C.metabolic	2.37568	0.702426	3.38211	0.0009

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	90.2316	1	90.2316	11.44	0.0009
Residual	1254.24	159	7.8883		
Total (Corr.)	1344.47	160			

R-squared = 6.7113 percent

Metabolic explains 6.71% of the variability in Bacon, meaning the presence of a metabolic disorder correlates with a higher number of fixations before first fixating on the bacon.

Dependent variable: Loin
Independent variables:
  C.inc_meds
Selection variable: C.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	6.88398	1.19965	5.73833	0.0000
C.inc_meds	-1.80698	0.625614	-2.88832	0.0044

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	58.7323	1	58.7323	8.34	0.0044
Residual	1119.39	159	7.0402		
Total (Corr.)	1178.12	160			

R-squared = 4.98524 percent

Inc_meds explains 4.99% of the variability in Loin, meaning people not taking appetite-increasing medication have a lower number of fixations before first fixating on the lean loin.

Grapes-Candy

Dependent variable: Candy
Independent variables:
Grapes
D.allergy
D.habits
D.gender
D.prot_lip
Selection variable: D.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	3.13087	1.0596	2.95477	0.0036
Grapes	-0.343461	0.101412	-3.3868	0.0009
D.allergy	-0.783503	0.45515	-1.72142	0.0872
D.habits	0.513259	0.298695	1.71834	0.0878
D.gender	0.546022	0.306007	1.78435	0.0763
D.prot_lip	0.665702	0.330234	2.01585	0.0456

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	112.256	5	22.4512	6.62	0.0000
Residual	518.926	153	3.39168		
Total (Corr.)	631.182	158			

R-squared = 17.785 percent

A model comprised of Grapes, allergy, habits, gender and prot_lip explains 17.79% of the variability in Candy, with Grapes and prot_lip showing a significant interaction at the 95% confidence level, meaning a person with a preference for proteins and lipids will have a higher number of fixations before first fixating on the candy.

Burger-Wrap

Dependent variable: Burger
Independent variables:
E.age
Selection variable: E.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	0.240592	0.579302	0.415314	0.6785
E.age	0.0722837	0.0184214	3.92389	0.0001

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	116.816	1	116.816	15.40	0.0001
Residual	1191.16	157	7.587		
Total (Corr.)	1307.97	158			

R-squared = 8.93109 percent

Age explains 8.93% of the variability in Burger, meaning a higher age correlates with a higher number of fixations before first fixating on the cheeseburger.

Cookie-Roll

There are no significant relationships between the AOIs and other parameters.

Chips-Banana

Dependent variable: Chips
Independent variables:
Banana
G.BMI
Selection variable: G.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	1.9702	0.729154	2.70203	0.0077
Banana	-0.311131	0.0846509	-3.67546	0.0003
G.BMI	0.0456475	0.0231684	1.97025	0.0506

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	129.553	2	64.7763	9.33	0.0001
Residual	1075.97	155	6.94172		
Total (Corr.)	1205.52	157			

R-squared = 10.7466 percent

A model comprised of Banana and BMI explains 10.75% of the variability in Chips, meaning a person with a higher BMI will have a higher number of fixations before first fixating on the potato chips (the P-value for this interaction is 0.0506, i.e. slightly below the 95% confidence level).

Dependent variable: Banana
Independent variables:
Chips
G.allergy
G.prot_lip
Selection variable: G.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	5.57929	1.17365	4.75379	0.0000
Chips	-0.239636	0.0681174	-3.51799	0.0006
G.allergy	-1.29191	0.592935	-2.17884	0.0309
G.prot_lip	0.812879	0.41276	1.96937	0.0507

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	132.608	3	44.2027	8.08	0.0000
Residual	842.309	154	5.46954		
Total (Corr.)	974.918	157			

R-squared = 13.602 percent

A model comprised of Chips, allergy and prot_lip explains 12.6% of the variability in Banana, meaning a preference for proteins and lipids correlates with a higher number of fixations before first fixating on the banana chips, while a lack of allergies and food intolerances correlates with a lower number.

Notes

Interestingly, there is no statistically significant interaction between the AOIs for 3 out of 6 images.

5.5.4 Fixation Count

Tomato-Salami

Dependent variable: Tomato
Independent variables:
A.inc_meds
A.metabolic
A.age
A.BMI
Selection variable: A.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	11.8991	2.85875	4.16233	0.0001
A.inc_meds	0.377147	1.07862	0.349656	0.7271
A.metabolic	-1.27106	1.11485	-1.14012	0.2560
A.age	-0.0351038	0.0312678	-1.12268	0.2633
A.BMI	-0.0373146	0.0433754	-0.860271	0.3910

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	165.542	4	41.3856	3.00	0.0204
Residual	2125.38	154	13.8011		
Total (Corr.)	2290.92	158			

R-squared = 7.22603 percent

A model comprised of inc_meds, metabolic, age and BMI explains 7.23% of the variability in Tomato, although none of these factors have a P-value below 0.05.

Avocado-Cucumber

Dependent variable: Avocado
Independent variables:
B.allergy
B.inc_meds
B.age
B.BMI
Selection variable: B.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	8.27926	2.986	2.77269	0.0062
B.allergy	1.91833	0.828364	2.3158	0.0219
B.inc_meds	-0.0120775	0.973162	-0.0124106	0.9901
B.age	-0.0295406	0.0265521	-1.11255	0.2676
B.BMI	-0.0808957	0.0385503	-2.09845	0.0375

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	208.474	4	52.1186	4.64	0.0015
Residual	1730.48	154	11.2369		
Total (Corr.)	1938.96	158			

R-squared = 10.7519 percent

A model comprised of allergy, inc_meds, age and BMI explains 10.75% of the variability in Avocado, with allergy and BMI both showing statistical significance at the 95% confidence level (the number of fixations tends to be lower in people with higher BMIs and higher in those without allergies or food intolerances)

Bacon-Loin

Dependent variable: Bacon
Independent variables:
    C.inc_meds
    C.age
    C.BMI
Selection variable: C.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	11.1796	2.83208	3.94749	0.0001
C.inc_meds	0.138805	1.08088	0.128419	0.8980
C.age	-0.0215012	0.0299201	-0.718621	0.4735
C.BMI	-0.0928063	0.0422132	-2.19851	0.0294

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	170.864	3	56.9546	4.22	0.0067
Residual	2090.13	155	13.4847		
Total (Corr.)	2260.99	158			

R-squared = 7.55702 percent

A model comprised of inc_meds, age and BMI explains 7.56% of the variability in Bacon, with BMI showing statistical significance at the 95% confidence level (the number of fixations on the bacon tends to be lower in people with higher Body Mass Indices).

Dependent variable: Loin
Independent variables:
    C.allergy
Selection variable: C.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	5.93459	1.56089	3.80205	0.0002
C.allergy	1.69699	0.817959	2.07467	0.0396

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	48.1775	1	48.1775	4.30	0.0396
Residual	1757.31	157	11.193		
Total (Corr.)	1805.48	158			

R-squared = 2.6684 percent

Allergy explains 2.67% of the variability in Loin, meaning people without allergies generally have a higher number of fixations on the lean loin.

Grapes-Candy

Dependent variable: Grapes
Independent variables:
    D.inc_meds
    D.metabolic
    D.age
    D.BMI
Selection variable: D.ratio

		Standard	T	
Parameter	Estimate	Error	Statistic	P-Value
CONSTANT	8.63372	2.82501	3.05617	0.0026
D.inc_meds	1.0731	1.06673	1.00598	0.3160
D.metabolic	-1.52514	1.10259	-1.38323	0.1686
D.age	-0.01993	0.0309006	-0.644971	0.5199
D.BMI	-0.0308167	0.0428575	-0.719051	0.4732

Analysis of Variance

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Model	175.197	4	43.7993	3.24	0.0137
Residual	2105.91	156	13.4994		
Total (Corr.)	2281.11	160			

R-squared = 7.68036 percent

A model comprised of inc_meds, metabolic, age and BMI explains 7.68% of the variability in Grapes, although none of the factors show a statistical significance on the 95% confidence level.

Dependent variable: Candy
Independent variables:
D.meat
D.metabolic
Selection variable: D.ratio

		Standard	T	
Parameter	Estimate	Error	Statistic	P-Value
CONSTANT	10.5498	1.52671	6.91013	0.0000
D.meat	-1.75408	0.78727	-2.22805	0.0273
D.metabolic	1.43015	0.70395	2.03161	0.0439

Analysis of Variance

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Model	74.2107	2	37.1054	4.69	0.0105
Residual	1250.61	158	7.91525		
Total (Corr.)	1324.82	160			

R-squared = 5.60157 percent

A model comprised of meat and metabolic explains 5.6% of the variability in Candy, with both factors showing statistical significance on the 95% confidence level, meaning that eating meat correlates with a lower number of fixations on the candy, while the presence of a metabolic disorder is correlated with a higher fixation count.

Burger-Wrap

Dependent variable: Burger
Independent variables:
E.inc_meds
E.gender
E.age
Selection variable: E.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	5.83036	2.21096	2.63702	0.0092
E.inc_meds	1.06666	0.90161	1.18306	0.2386
E.gender	1.25664	0.563524	2.22996	0.0272
E.age	-0.0409073	0.0257286	-1.58995	0.1139

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	160.427	3	53.4756	4.50	0.0047
Residual	1840.97	155	11.8772		
Total (Corr.)	2001.4	158			

R-squared = 8.01574 percent

A model comprised of inc_meds, gender and age explains 8.02% of the variability in Burger, with gender showing statistical significance on the 95% confidence level, meaning that males tend to have a higher number of fixations of the burger.

Cookie-Roll

Dependent variable: Roll
Independent variable: F.BMI
Linear model: Y = a + b*X

Coefficients

	Least Squares	*Standard*	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
Intercept	12.926	0.965796	13.3838	0.0000
Slope	-0.0898541	0.0337725	-2.66057	0.0086

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	113.045	1	113.045	7.08	0.0086
Residual	2539.2	159	15.9698		
Total (Corr.)	2652.25	160			

R-squared = 4.26222 percent

The Body Mass Index explains 4.26% of the variability in Roll (meaning that people with higher Body Mass Indices tend to have a lower number of fixations on the pumpkin seed roll.

Chips-Banana

Dependent variable: Banana
Independent variables:
G.inc_meds
G.BMI
Selection variable: G.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	9.73121	2.98097	3.26445	0.0013
G.inc_meds	1.59428	1.15692	1.37805	0.1702
G.BMI	-0.0415601	0.0412834	-1.0067	0.3156

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	103.005	2	51.5027	3.29	0.0400
Residual	2444.1	156	15.6673		
Total (Corr.)	2547.11	158			

R-squared = 4.04402 percent

A model comprised of inc_meds and BMI explains 4.04% of the variability in Banana, although there is no proof of statistical significance above the 95% confidence level for the individual factors.

Notes

Interestingly, there is no statistically significant interaction between the AOIs for 3 out of 6 images.

5.5.5 Fixation Length

Tomato-Salami

Dependent variable: Tomato
Independent variables:
    Salami
    A.inc_meds
    A.metabolic
    A.age
    A.BMI
Selection variable: A.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	5.99916	0.791739	7.57719	0.0000
Salami	-0.694269	0.0749176	-9.26709	0.0000
A.inc_meds	0.242755	0.290939	0.834383	0.4054
A.metabolic	0.0293662	0.301191	0.0975005	0.9225
A.age	-0.0235871	0.00845019	-2.79131	0.0059
A.BMI	-0.0061451	0.0117362	-0.523601	0.6013

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	108.883	5	21.7766	21.70	0.0000
Residual	153.561	153	1.00367		
Total (Corr.)	262.444	158			

R-squared = 41.4881 percent

A model comprised of Salami, inc_meds, metabolic, age and BMI explains 41.49% of the variability in Tomato, with Salami and age having a P-value below 0.05, meaning that older participants tend to spend less time looking at the tomatoes, and that more time spent fixating on the salami means less time spent on the tomatoes.

Dependent variable: Salami
Independent variables:
    Tomato
    A.gender
    A.carbs
Selection variable: A.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	4.38211	0.344904	12.7053	0.0000
Tomato	-0.468655	0.0541077	-8.66153	0.0000
A.gender	0.171565	0.143225	1.19788	0.2328
A.carbs	-0.224991	0.162907	-1.3811	0.1692

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	64.8637	3	21.6212	28.78	0.0000
Residual	116.434	155	0.751189		
Total (Corr.)	181.298	158			

R-squared = 35.7774 percent

A model comprised of Tomato, gender and carbs explains 35.78% of the variability in Salami, with Tomato having a P-value below 0.05, meaning more time spent fixated on the tomatoes results in less time fixated on the salami.

Avocado-Cucumber

Dependent variable: Avocado
Independent variables:
    Cucumber
    B.inc_meds
    B.metabolic
    B.age
    B.BMI
Selection variable: B.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	5.86212	0.780314	7.51252	0.0000
Cucumber	-0.555719	0.0696463	-7.97916	0.0000
B.inc_meds	0.102555	0.283395	0.361881	0.7179
B.metabolic	-0.362295	0.29303	-1.23638	0.2182
B.age	-0.0182988	0.00826366	-2.21437	0.0283
B.BMI	-0.0214802	0.0114313	-1.87907	0.0621

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	86.6785	5	17.3357	18.21	0.0000
Residual	145.664	153	0.952052		
Total (Corr.)	232.342	158			

R-squared = 37.3063 percent

A model comprised of Cucumber, inc_meds, metabolic, age and BMI explains 37.3% of the variability in Avocado, with Cucumber and age both showing statistical significance at the 95% confidence level, meaning that older participants tend to spend less time looking at the avocado, and that more time spent fixating on the avocado means less time spent on the cucumber.

Bacon-Loin

Dependent variable: Bacon
Independent variables:
    Loin
    C.inc_meds
    C.BMI
Selection variable: C.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	4.54656	0.789477	5.75895	0.0000
Loin	-0.548707	0.070762	-7.75426	0.0000
C.inc_meds	0.367112	0.294949	1.24466	0.2151
C.BMI	-0.0180919	0.0105157	-1.72047	0.0873

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	72.381	3	24.127	23.80	0.0000
Residual	157.099	155	1.01354		
Total (Corr.)	229.48	158			

R-squared = 31.5413 percent

A model comprised of Loin, inc_meds, and BMI explains 31.54% of the variability in Bacon, with Loin showing statistical significance at the 95% confidence level.

Grapes-Candy

Dependent variable: Grapes
Independent variables:
Candy
D.inc_meds
D.metabolic
D.age
D.BMI
Selection variable: D.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	4.92643	0.820559	6.00376	0.0000
Candy	-0.532776	0.0799092	-6.66726	0.0000
D.inc_meds	0.252075	0.296734	0.849499	0.3969
D.metabolic	-0.335617	0.308101	-1.08931	0.2777
D.age	-0.0133998	0.00860725	-1.5568	0.1216
D.BMI	0.00440966	0.011911	0.370216	0.7117

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	67.3881	5	13.4776	12.93	0.0000
Residual	161.616	155	1.04268		
Total (Corr.)	229.004	160			

R-squared = 29.4266 percent

A model comprised of Candy, inc_meds, metabolic, age and BMI explains 29.43% of the variability in Grapes, with Candy being the most influential factor.

Dependent variable: Candy
Independent variables:
Grapes
D.meat
D.metabolic
D.age
Selection variable: D.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	5.24671	0.573546	9.14784	0.0000
Grapes	-0.408369	0.0619725	-6.58953	0.0000
D.meat	-0.458069	0.251691	-1.81997	0.0707
D.metabolic	0.203139	0.262452	0.774004	0.4401
D.age	0.0000911344	0.00702752	0.0129682	0.9897

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	46.3597	4	11.5899	14.54	0.0000
Residual	124.331	156	0.796994		
Total (Corr.)	170.691	160			

R-squared = 27.16 percent

A model comprised of Grapes, meat, metabolic and age explains 27.16% of the variability in Candy, with Grapes being the most influential factor (P-value 0.0000). Meat has a P-value of 0.0707, meaning there is a statistically significant influence of whether the participant consumes meat (meat-eaters spend less time looking at the candy).

Burger-Wrap

Dependent variable: Burger
Independent variables:
 Wrap
 E.gender
Selection variable: E.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	4.72502	0.348617	13.5536	0.0000
Wrap	-0.609694	0.0646819	-9.42604	0.0000
E.gender	0.354242	0.144928	2.44426	0.0156

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	82.5511	2	41.2756	51.74	0.0000
Residual	124.456	156	0.797797		
Total (Corr.)	207.007	158			

R-squared = 39.8783 percent

A model comprised of Wrap and gender explains 39.88% of the variability in Burger, with Wrap and gender showing statistical significance on the 95% confidence level, meaning that males tend to spend more time looking at the cheeseburger.

Cookie-Roll

Dependent variable: Roll
Independent variables:
 Cookie
 F.inc_meds
 F.gender
 F.BMI
Selection variable: F.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	4.23312	0.714172	5.92731	0.0000
Cookie	-0.605004	0.0702941	-8.60675	0.0000
F.inc_meds	0.403575	0.26855	1.50279	0.1349
F.gender	0.364627	0.148067	2.46257	0.0149
F.BMI	-0.00361303	0.00949049	-0.3807	0.7040

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	78.4137	4	19.6034	23.82	0.0000
Residual	126.755	154	0.823086		
Total (Corr.)	205.169	158			

R-squared = 38.2191 percent

A model comprised of Cookie, inc_meds and gender explains 38.22% of the variability in Roll, with Cookie and gender showing statistical significance on the 95% confidence level, meaning that males tend to spend more time looking at the pumpkin seed roll.

Chips-Banana

Dependent variable: Banana
Independent variables:
 Chips
 G.satiety
Selection variable: G.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	6.06439	0.256903	23.6058	0.0000
Chips	-0.61825	0.0625907	-9.87766	0.0000
G.satiety	-0.247174	0.108333	-2.28161	0.0239

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	79.0272	2	39.5136	52.05	0.0000
Residual	118.416	156	0.759078		
Total (Corr.)	197.443	158			

R-squared = 40.0253 percent

A model comprised of Chips and satiety explains 40.03% of the variability in Banana, with both showing evidence of a statistical relationship at the 95% confidence level, meaning hungry people tend to spend less time looking at the banana chips.

Notes

The P-values for the statistical relationships between the AOIs are all 0.0000, supporting the obvious assumption that the time spent looking on one AOI is inversely proportional to the time spent looking at the other.

5.5.6 Observation Count

Tomato-Salami

Dependent variable: Tomato
Independent variables:
Salami
A.allergy
A.age
Selection variable: A.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	0.899771	0.487051	1.84738	0.0666
Salami	0.546367	0.0686431	7.95952	0.0000
A.allergy	0.223913	0.246178	0.909556	0.3645
A.age	0.00617146	0.00672803	0.917276	0.3604

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	72.0334	3	24.0111	24.54	0.0000
Residual	151.677	155	0.978563		
Total (Corr.)	223.711	158			

R-squared = 32.1994 percent

A model comprised of Salami, allergy, and age explains 32.2% of the variability in Tomato, with only Salami showing significance at the 95% confidence level (P-value = 0.0000). Interestingly, a high observation count is directly correlated with a high observation count for the other AOI.

Dependent variable: Salami
Independent variables:
Tomato
A.habits
A.metabolic
A.mood
A.allergy
A.age
Selection variable: A.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	2.16335	0.66779	3.23957	0.0015
Tomato	0.493127	0.064632	7.62977	0.0000
A.habits	-0.356326	0.149193	-2.38835	0.0182
A.metabolic	0.369637	0.273893	1.34957	0.1792
A.mood	-0.614403	0.213045	-2.88391	0.0045
A.allergy	0.189661	0.232809	0.81466	0.4165
A.age	0.00423839	0.00731717	0.579239	0.5633

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	86.0937	6	14.349	16.48	0.0000
Residual	132.334	152	0.870618		
Total (Corr.)	218.428	158			

R-squared = 39.4152 percent

A model comprised of Tomato, habits, metabolic, mood, allergy and age explains 39.42% of the variability in Salami, with Tomato being the most important factor (P-value = 0.0000), followed by mood (P=0.0045) and habits (P=0.0182). In other words, a relaxed mood and a preference for fewer but more extensive meals are correlated with a lower number of fixations on the salami

Avocado-Cucumber

Dependent variable: Avocado
Independent variables:
- B.allergy
- B.inc_meds
- B.age
- B.BMI

Selection variable: B.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	7.17297	2.63751	2.7196	0.0073
B.allergy	1.64402	0.731686	2.24689	0.0261
B.inc_meds	0.135264	0.859585	0.157359	0.8752
B.age	-0.0293397	0.0234532	-1.25099	0.2128
B.BMI	-0.0735277	0.0340511	-2.15933	0.0324

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	181.209	4	45.3023	5.17	0.0006
Residual	1350.12	154	8.76704		
Total (Corr.)	1531.33	158			

R-squared = 11.8334 percent

A model comprised of allergy, inc_meds, age and BMI explains 11.83% of the variability in Avocado, with allergy and BMI both showing statistical significance at the 95% confidence level (the number of observations for the avocado tends to be lower in older people and in higher those without allergies or food intolerances).

Dependent variable: Cucumber
Independent variables:
- B.inc_meds
- B.BMI

Selection variable: B.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	7.5749	2.06513	3.668	0.0003
B.inc_meds	0.515253	0.796498	0.646898	0.5186
B.BMI	-0.0496094	0.0286486	-1.73165	0.0853

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	53.745	2	26.8725	3.55	0.0310
Residual	1179.81	156	7.56292		
Total (Corr.)	1233.56	158			

R-squared = 4.3569 percent

A model comprised of inc_meds and BMI explains 4.36% of the variability in Cucumber, with BMI being the factor with the lowest P-value (0.0853) – a higher BMI correlates with a lower observation count for the cucumber.

Bacon-Loin

Dependent variable: Loin
Independent variables:
Bacon
C.metabolic
Selection variable: C.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	1.18485	0.245177	4.83266	0.0000
Bacon	0.513985	0.082829	6.20537	0.0000
C.metabolic	0.867816	0.263435	3.29423	0.0012

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	51.2717	2	25.6358	25.73	0.0000
Residual	155.42	156	0.996283		
Total (Corr.)	206.692	158			

R-squared = 24.8059 percent

A model comprised of Bacon and metabolic explains 24.81% of the variability in Loin, with both showing significance well above the 95% level (the P-values being 0.0000 and 0.0012, respectively). The observation count for the lean loin increases with the observation count for the bacon and the presence of metabolic disorders.

Grapes-Candy

Dependent variable: Candy
Independent variables:
Grapes
D.habits
D.mood
D.age
Selection variable: D.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	1.58935	0.554126	2.86821	0.0047
Grapes	0.49275	0.0681394	7.23149	0.0000
D.habits	-0.306138	0.152125	-2.01241	0.0459
D.mood	-0.300971	0.217506	-1.38374	0.1684
D.age	0.0160399	0.00637182	2.51732	0.0128

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	65.8917	4	16.4729	18.05	0.0000
Residual	142.344	156	0.912464		
Total (Corr.)	208.236	160			

R-squared = 31.6428 percent

A model comprised of Grapes, habits mood and age explains 31.64% of the variability in Candy, with all factors except mood show a statistical significance on the 95% confidence level. The number of observations for the hard candy increases with a high number of observations for the Grapes as well as in older people and decreases in people with a tendency towards smaller but extensive meals.

Burger-Wrap

Dependent variable: Burger
Independent variables:
Wrap
E.allergy
E.mood
Selection variable: E.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	1.07327	0.642679	1.66999	0.0969
Wrap	0.57721	0.053416	10.8059	0.0000
E.allergy	0.460344	0.2363	1.94813	0.0532
E.mood	-0.408064	0.220535	-1.85034	0.0662

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	129.159	3	43.0529	46.42	0.0000
Residual	143.76	155	0.927481		
Total (Corr.)	272.918	158			

R-squared = 47.325 percent

A model comprised of Wrap, allergy and mood explains 47.33% of the variability in Burger, with Wrap showing statistical significance on the 95% confidence level, and P-values of 0.0532 and 0.0662 for allergy and mood, respectively. In other words a high observation count for the cheeseburger is related to a high observation count for the grilled chicken wrap, an absence of allergies and negatively correlated with a relaxed mood.

Cookie-Roll

Dependent variable: Cookie
Independent variables:
Roll
F.mood
Selection variable: F.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	1.90557	0.498001	3.82643	0.0002
Roll	0.515489	0.0598705	8.61007	0.0000
F.mood	-0.353441	0.227754	-1.55186	0.1227

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	83.9433	2	41.9717	43.10	0.0000
Residual	151.906	156	0.973755		
Total (Corr.)	235.849	158			

R-squared = 35.592 percent

A model comprised of Roll and mood explains 35.59% of the variability in Cookie, with Roll showing a P-value of 0.000 and Cookie having a P-Value of 0.1227.

Dependent variable: Roll
Independent variables:
Cookie
F.mood
F.age
Selection variable: F.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	1.40909	0.576471	2.44433	0.0156
Cookie	0.611865	0.0717845	8.52363	0.0000
F.mood	-0.344287	0.247862	-1.38903	0.1668
F.age	0.016725	0.00716908	2.33294	0.0209

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	106.79	3	35.5966	31.01	0.0000
Residual	177.902	155	1.14775		
Total (Corr.)	284.692	158			

R-squared = 37.5107 percent

A model comprised of Cookie, mood and age explains 37.51% of the variability in Roll, with Cookie and age both showing a statistical relationship at the 95% confidence level. In other words, the observation count for the pumpkin seed roll is positively related to the observation count for the cookie and a higher age, and tends to decrease with a relaxed mood.

Chips-Banana

Dependent variable: Chips
Independent variables:
Banana
Selection variable: G.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	1.57665	0.175648	8.97619	0.0000
Banana	0.398363	0.0605047	6.584	0.0000

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	36.5893	1	36.5893	43.35	0.0000
Residual	132.518	157	0.844061		
Total (Corr.)	169.107	158			

R-squared = 21.6368 percent

The observation count for the potato chips is positively correlated with a higher observation count for the banana chips.

Notes

With the exception of Avocado-Cucumber, the observation counts for both AOIs are strongly positively correlated (with P-values of 0.0000), i.e. just the opposite relationship that we see with fixation lengths. This was to be expected, as an “observation” is defined from the time elapsed between the first fixation within a specific AOI to the first fixation outside that AOI (which can reasonably be expected to be located either within or on the way to the other AOI).

In an image comprised of two areas of interest, observation count is thus more valuable as an indicator of a participant's tendency to shift their point of gaze between AOIs, rather than a measure of preference.

The reason for the results of Avocado-Cucumber differing from the rest is again most likely the fact that it involves "split" AOIs.

5.5.7 Observation Length

Tomato-Salami

Dependent variable: Tomato
Independent variables:
- Salami
- A.inc_meds
- A.age
- A.metabolic
- A.BMI

Selection variable: A.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	6.18403	0.809054	7.64353	0.0000
Salami	-0.716659	0.0748025	-9.58068	0.0000
A.inc_meds	0.252552	0.297094	0.850074	0.3966
A.age	-0.0242893	0.00862812	-2.81514	0.0055
A.metabolic	0.106799	0.308046	0.346698	0.7293
A.BMI	-0.00532438	0.0119775	-0.444534	0.6573

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	118.41	5	23.682	22.63	0.0000
Residual	160.123	153	1.04656		
Total (Corr.)	278.533	158			

R-squared = 42.5121 percent

A model comprised of Salami, inc_meds, metabolic, age and BMI explains 42.51% of the variability in Tomato, with Salami and age having a P-value below 0.05, meaning that older participants tend to spend less time looking at the tomatoes, and that more time spent fixating on the salami means less time spent on the tomatoes.

Dependent variable: Salami
Independent variables:
- A.carbs
- Tomato

Selection variable: A.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	4.83848	0.234933	20.5951	0.0000
A.carbs	-0.248633	0.161272	-1.5417	0.1252
Tomato	-0.486098	0.052872	-9.19388	0.0000

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	69.8501	2	34.9251	45.30	0.0000
Residual	120.276	156	0.770999		
Total (Corr.)	190.126	158			

R-squared = 36.7389 percent

A model comprised of Tomato, gender and carbs explains 36.74% of the variability in Salami, with Tomato having a P-value below 0.05, meaning more time spent fixated on the tomatoes results in less time fixated on the salami.

Avocado-Cucumber

Dependent variable: Avocado
Independent variables:
    B.metabolic
    B.prot_lip
    B.age
    B.BMI
Selection variable: B.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	3.02985	0.328358	9.22729	0.0000
B.metabolic	-0.409991	0.340693	-1.20341	0.2311
B.prot_lip	-0.364714	0.185034	-1.97106	0.0509
B.age	-0.0063966	0.00922405	-0.69347	0.4893
B.BMI	-0.0150199	0.0104473	-1.43767	0.1530

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	12.6207	4	3.15517	3.61	0.0081
Residual	109.291	125	0.874331		
Total (Corr.)	121.912	129			

R-squared = 10.3523 percent

A model comprised of metabolic, prot_lip, age and BMI explains 10.35% of the variability in Avocado, with prot_lip having the lowest P-value at 0.0509, i.e. just below the 95% confidence level. In other words, a preference for proteins and lipids seems to correlate with a higher observation length for the Avocado. Interestingly, there does not seem to be any relationship between the two AOIs as would have been expected.

Bacon-Loin

Dependent variable: Bacon
Independent variables:
    Loin
    C.inc_meds
    C.BMI
Selection variable: C.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	4.78657	0.755788	6.33321	0.0000
Loin	-0.610704	0.0648667	-9.41476	0.0000
C.inc_meds	0.422704	0.282398	1.49684	0.1365
C.BMI	-0.0138325	0.0100824	-1.37195	0.1721

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	94.2362	3	31.4121	33.80	0.0000
Residual	144.045	155	0.92932		
Total (Corr.)	238.281	158			

R-squared = 39.5484 percent

A model comprised of Loin, inc_meds, and BMI explains 39.55% of the variability in Bacon, with Loin showing statistical significance at the 95% confidence level.

Grapes-Candy

Dependent variable: Grapes
Independent variables:
Candy
D.inc_meds
D.metabolic
D.prot_lip
D.age
D.BMI
Selection variable: D.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	5.30667	0.8145	6.51525	0.0000
Candy	-0.574533	0.0770431	-7.45729	0.0000
D.inc_meds	0.298431	0.296327	1.0071	0.3155
D.metabolic	-0.355994	0.306868	-1.16009	0.2478
D.prot_lip	-0.32477	0.179305	-1.81127	0.0720
D.age	-0.0116732	0.00862644	-1.35319	0.1780
D.BMI	0.00506363	0.0118703	0.426578	0.6703

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	87.0222	6	14.5037	14.01	0.0000
Residual	159.384	154	1.03496		
Total (Corr.)	246.406	160			

R-squared = 35.3166 percent

A model comprised of Candy, inc_meds, metabolic, prot_lip, age and BMI explains 35.32% of the variability in Grapes, with Candy (P-value 0.000) being the most influential factor, followed by prot_lip at 0.0720 – a preference for proteins and lipids seems to correlate with more time spent observing the grapes.

Dependent variable: Candy
Independent variables:
Grapes
D.meat
D.metabolic
D.age
Selection variable: D.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	5.57739	0.576831	9.66901	0.0000
Grapes	-0.449157	0.0600653	-7.47781	0.0000
D.meat	-0.495575	0.252306	-1.96418	0.0513
D.metabolic	0.141732	0.263274	0.538343	0.5911
D.age	0.00141832	0.00705742	0.200969	0.8410

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	58.9216	4	14.7304	18.38	0.0000
Residual	125.054	156	0.801629		
Total (Corr.)	183.976	160			

R-squared = 32.0268 percent

A model comprised of Grapes, meat, metabolic and age explains 32.03% of the variability in Candy, with Grapes being the most influential factor (P-value 0.0000), followed by meat with a P-Value slightly above 0.05 (meat-eaters spend less time looking at the candy).

Burger-Wrap

Dependent variable: Burger
Independent variables:
  Wrap
  E.gender
Selection variable: E.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	5.29664	0.341881	15.4926	0.0000
Wrap	-0.676208	0.0606102	-11.1567	0.0000
E.gender	0.269576	0.138628	1.9446	0.0536

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	101.377	2	50.6887	70.32	0.0000
Residual	112.448	156	0.720823		
Total (Corr.)	213.826	158			

R-squared = 47.4112 percent

A model comprised of Wrap and gender explains 47.41% of the variability in Burger, with Wrap and showing statistical significance at the 95% confidence level and gender having a P-value of 0.0536 (i.e. just short of the 95% confidence level) meaning that males tend to spend more time looking at the cheeseburger.

Cookie-Roll

Dependent variable: Roll
Independent variables:
  Cookie
  F.inc_meds
  F.gender
  F.BMI
Selection variable: F.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	4.64449	0.704817	6.58964	0.0000
Cookie	-0.632318	0.0649319	-9.73816	0.0000
F.inc_meds	0.389859	0.264166	1.47581	0.1420
F.gender	0.283167	0.146089	1.93831	0.0544
F.BMI	-0.00281295	0.00932907	-0.301526	0.7634

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	91.6641	4	22.916	28.77	0.0000
Residual	122.65	154	0.796429		
Total (Corr.)	214.314	158			

R-squared = 42.7709 percent

A model comprised of Cookie, inc_meds and gender explains 42.77% of the variability in Roll, with Cookie with P-values of 0.0000 for Cookie and 0.0544 and for gender, meaning that males tend to spend more time looking at the pumpkin seed roll.

Chips-Banana

Dependent variable: Banana

Independent variables:
Chips
G.satiety
Selection variable: G.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	6.42833	0.24219	26.5425	0.0000
Chips	-0.681994	0.0573752	-11.8866	0.0000
G.satiety	-0.250064	0.102385	-2.4424	0.0157

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	101.369	2	50.6843	74.80	0.0000
Residual	105.708	156	0.677614		
Total (Corr.)	207.077	158			

R-squared = 48.9523 percent

A model comprised of Chips and satiety explains 48.95% of the variability in Banana, with both showing evidence of a statistical relationship at the 95% confidence level, meaning hungry people tend to spend less time looking at the banana chips.

Notes

As with Fixation Length, there is clear evidence of a statistical relationship (a P-value of 0.0000) between the AOIs, i.e. a higher observation length for one AOI correlates with a smaller observation length for the other. Avocado-Cucumber is the clear exception, which is most likely related to the fact that in this image, the AOIs are “split” (i.e. both avocado and cucumber are each represented by two AOIs carrying the same name).

5.5.8 Time to First Fixation

Tomato-Salami

Dependent variable: Salami
Independent variables:
Tomato
A.prot_lip
Selection variable: A.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	1.30562	0.1871	6.97818	0.0000
Tomato	-0.404707	0.118376	-3.41882	0.0008
A.prot_lip	0.453942	0.196762	2.30706	0.0224

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	21.7021	2	10.8511	8.71	0.0003
Residual	193.001	155	1.24517		
Total (Corr.)	214.703	157			

R-squared = 10.108 percent

A model comprised of Tomato and prot_lip explains 10.11% of the variability in Salami, with both showing a significant relationship at the 95% confidence level (a lower TTFF for the tomatoes and a preference for proteins is related to a higher TTFF for the salami).

Avocado-Cucumber

Dependent variable: Cucumber
Independent variables:
Avocado
B.prot_lip
Selection variable: B.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	1.52726	0.148607	10.2771	0.0000
Avocado	-0.627185	0.101198	-6.19759	0.0000
B.prot_lip	0.34576	0.152375	2.26914	0.0246

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	33.595	2	16.7975	22.47	0.0000
Residual	116.616	156	0.74754		
Total (Corr.)	150.211	158			

R-squared = 22.3652 percent

A model comprised of Avocado and prot_lip explains 22.37% of the variability in Cucumber, with both showing a significant relationship at the 95% confidence level (a lower TTFF for the avocado and a preference for proteins is related to a higher TTFF for the cucumber).

Bacon-Loin

Dependent variable: Loin
Independent variables:
C.inc_meds
Bacon

Selection variable: C.ratio

		Standard	T	
Parameter	Estimate	Error	Statistic	P-Value
CONSTANT	2.39779	0.413916	5.79293	0.0000
C.inc_meds	-0.620084	0.215838	-2.87292	0.0046
Bacon	-0.300419	0.107725	-2.78877	0.0059

Analysis of Variance

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Model	13.9025	2	6.95127	8.75	0.0003
Residual	124.002	156	0.794882		
Total (Corr.)	137.904	158			

R-squared = 10.0813 percent

A model comprised of inc_meds and Bacon explains 10.08% of the variability in Loin, with both showing a significant relationship at the 95% confidence level (a lower TTFF for the bacon and taking appetite-increasing medication is related to a higher TTFF for the lean loin).

Grapes-Candy

Dependent variable: Candy
Independent variables:
D.allergy
D.prot_lip
Selection variable: D.ratio

		Standard	T	
Parameter	Estimate	Error	Statistic	P-Value
CONSTANT	1.81354	0.421037	4.30731	0.0000
D.allergy	-0.528603	0.209934	-2.51795	0.0128
D.prot_lip	0.306983	0.15005	2.04587	0.0424

Analysis of Variance

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Model	8.24188	2	4.12094	5.61	0.0044
Residual	115.404	157	0.735057		
Total (Corr.)	123.646	159			

R-squared = 6.66571 percent

A model comprised of allergy and prot_lip explains 6.67% of the variability in Candy, with both showing a significant relationship at the 95% confidence level (the presence of allergies are related to a lower TTFF for the candies, a preference for proteins and lipids relates to a higher TTFF for the candies).

Burger-Wrap

Dependent variable: Burger
Independent variables:
Wrap
E.age
Selection variable: E.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	0.541076	0.22988	2.35373	0.0198
Wrap	-0.409745	0.101992	-4.01741	0.0001
E.age	0.0191862	0.00685811	2.79759	0.0058

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	23.864	2	11.932	12.19	0.0000
Residual	150.682	154	0.978453		
Total (Corr.)	174.546	156			

R-squared = 13.6721 percent

A model comprised of Wrap and age explains 13.67% of the variability in Burger, with both showing a significant relationship at the 95% confidence level (a lower TTFF for the wrap and a higher age is related to a higher TTFF for the cheeseburger).

Dependent variable: Wrap
Independent variables:
Burger
E.inc_meds
Selection variable: E.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	1.79321	0.339425	5.2831	0.0000
Burger	-0.215968	0.055381	-3.89967	0.0001
E.inc_meds	-0.431463	0.176631	-2.44274	0.0157

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	11.9201	2	5.96005	11.17	0.0000
Residual	82.1719	154	0.533584		
Total (Corr.)	94.092	156			

R-squared = 12.6686 percent

A model comprised of Burger and inc_meds explains 12.67% of the variability in Wrap, with both showing a significant relationship at the 95% confidence level (a lower TTFF for the cheeseburger and not taking appetite-increasing medication is related to a higher TTFF for the grilled chicken wrap.

Cookie-Roll

Dependent variable: Cookie
Independent variables:
F.carbs
Selection variable: F.ratio

		Standard	T	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	0.709927	0.101868	6.96909	0.0000
F.carbs	-0.24881	0.117754	-2.11297	0.0362

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	1.80687	1	1.80687	4.46	0.0362
Residual	61.9199	153	0.404705		
Total (Corr.)	63.7268	154			

R-squared = 2.83533 percent

A preference for carbohydrates is related to a lower TTFF for the cookie, explaining 2.84% of the variability in Cookie.

Chips-Banana

Dependent variable: Chips
Independent variables:
Banana
G.gender
G.BMI
Selection variable: G.ratio

		Standard	*T*	
Parameter	*Estimate*	*Error*	*Statistic*	*P-Value*
CONSTANT	-0.158102	0.302536	-0.522589	0.6020
Banana	-0.280939	0.078633	-3.57279	0.0005
G.gender	0.317435	0.135007	2.35125	0.0200
G.BMI	0.0217862	0.00724958	3.00516	0.0031

Analysis of Variance

Source	*Sum of Squares*	*Df*	*Mean Square*	*F-Ratio*	*P-Value*
Model	19.2078	3	6.40261	9.07	0.0000
Residual	109.46	155	0.706196		
Total (Corr.)	128.668	158			

R-squared = 14.9282 percent

A model comprised of Banana, gender and BMI explains 14.93% of the variability in Chips, with all three showing a significant relationship at the 95% confidence level (a lower TTFF for the Banana, a higher BMI and a male gender are related to a higher TTFF for the Chips).

Notes

In 5 out of 7 pictures, there was statistic evidence for an inverse relationship of the TTFF values for the two AOIs.

6 Conclusions and suggestions

6.1 Conclusions

Since all but one of the obese participants were recruited during the course of a medical treatment, mostly for obesity or obesity-related health issues, the statistical relationship between body mass index, medication and metabolic disorders is likely to be exaggerated. While the relationship between obesity and a wide variety of medical conditions is well-documented, one should keep in mind that our sample mostly represents those people who were prompted to seek medical help because of the severity of their condition. As such, the strong correlation between a high BMI and various metabolic disorders, appetite-increasing medication and an agitated mood can be assumed to have been strongly influenced by a selection bias. Similarly, when considering the relationship between BMI and age, one should take into account the fact that most of the normal-weight participants, being university students, were between 18 and 30 years of age (the mean age for the “BMI<30”-group was 24.58 years, while for the obese it was 41.86). However, a correlation between a higher age and increased BMI [121] and metabolic illnesses such as diabetes [122] certainly does exist, as does a correlation between BMI and depression, which may necessitate treatment with medication whose usually undesirable side effects include an increase in appetite [123].

The multiple regression analysis also showed a significant correlation ($p<0.05$) between gender and food preference – male subjects generally claimed to prefer protein-rich meals over carbohydrate-rich ones, again fitting in with previous research on this subject. [124]

In our analysis of the relationship between the BMI and the parameters Fixation Count and Fixation Length, we found that these were generally negatively correlated with a higher BMI. We were, however, unable to discern whether this phenomenon was caused by the BMI itself or the participants’ age with which it is correlated.

There is a strong tendency for participants to start at the left side of the screen when examining each image, as evidenced by the average Time to First Fixation for the left object being approximately half of that for the one on the right (however, the distance from the center of the screen/the fixation cross also plays a role, as shown by the image “Burger-Wrap”). A similar trend is shown by the parameter “Fixations Before”. The Observation Counts also tend to be slightly higher on the left side (with the exception of the image “Cookie-Roll”, where the left-side bias is offset by a significant difference in AOI size) – which is to be expected considering the left-side AOI usually has the advantage of being the first to be fixated on and thus also the first to be observed.

For the other parameters, such biases are not as clearly evident. Fixation Count, for example, seems to be mostly influenced by an AOI’s complexity rather than its position. The influence of a left-side bias can be expected to diminish if the participants are given sufficient time to fully explore the picture. Another factor worthy of investigation would be the influence of the position of the image in the sequence, e.g. trying to assess whether there are differences in how an image is perceived depending on whether it is placed near the start or the end of the sequence, and in how far the recording quality degrades over time due to shifts in sitting position, eye strain or a loss of mental focus.

At any rate, a left-sided bias is consistent with findings that show a strong preference for people to start scanning visual images from the top-left side [125-127]. In cultural environments where right-to-left script is used, such as the Arabic world, the opposite tends to be the case [128].

The simple regression analysis showed that the linear model is not ideally suited to describe the relationships between the ratios of two AOIs vs the BMI value. In general, the Reciprocal Y-Squared X model tended to yield the highest R^2 values for this purpose for the parameters Fixation Count, Fixation Length, Observation Count and Fixations Before, while the Squared Y-Reciprocal X model gave better results for First Fixation Duration and Time to First Fixation (it should be noted that for this thesis we used Statgraphics Centurion XV, which is capable of comparing a wider range of statistical models than the older version used in the previous experiment by Wallner [13]). However, the linear model does perform adequately for single AOIs vs BMI values.

An interesting finding concerning the image “Burger-Wrap” was that when questioned after the experiment, a large number of participants reported being drawn to the cheeseburger (which was selected as a visual cue due to its high fat content being clearly visible and for being devoid of “healthy” ingredients found in other burgers, such as tomatoes and lettuce) because they found it disgusting rather than appetizing. While a possible interpretation of this is that these people were simply in denial about their own dietary preferences, it fits in with recent findings by Haindl [129] that extremely unappealing foods tend to have greater attention-grabbing properties than appetizing ones (while Haindl’s work characterized the visual appeal of foods by their state of spoilage, it stands to reason that the same rules would apply to un-spoiled foods with negative emotional associations, such as a fear of heartburn or weight gain). Interestingly though, the mean summary observation and fixation lengths for the cheeseburger were significantly lower than those for the chicken wrap, even though both Areas of Interest had approximately the same size. One explanation for this is simply that due to its oblong shape, the wrap requires more eye movement than the roughly circular burger. However, there might also be a mechanism of conscious attention allocation at play, similar to what was suggested by Nijs [9]. This is somewhat supported by the fact that the

First Fixation Duration on the cheeseburger is significantly longer in high-BMI individuals, indicating a higher level of mental activity.

6.2 Suggestions for future studies

The questionnaire and/or participant variables in Tobii Studio should be designed with the future evaluation of the data in mind. Since some values will have to be entered in Excel or a similar program anyway (e.g. the exact age or weight, since Tobii® Studio – at least as of version 1.7.3 - does not allow for entering numeric values directly, instead requiring the user to pre-define a set of independent variables and values), one might consider not using Tobii® Studio's integrated participant management system at all. If possible, questions should involve answers ranked on a scale; one should also take care that the numeric values corresponding to the answers follow the same order for different variables and that the variable name is not misleading (for example, in this paper the parameter "satiety" was rated from 1 = full to 3 = hungry; in hindsight, we should either have used a different variable name, e.g. "hunger", or reversed the order of the answers).

As mentioned in the chapter "Questionnaire" under Materials and Methods, one should take care to avoid ambiguities, especially if the experiment requires the participants to fill out the questionnaire unsupervised. In this study, participants were free to ask us for clarification if a question was unclear, based on which we updated the questionnaire (see chapter 4.7).

Since eye tracking studies are conducted regularly at the University of Natural Resources and Life Sciences, usually involving more than a hundred participants each, a significant percentage of the student body from which the majority of test subjects are recruited is likely to have previously participated in one or more such experiments. Future studies should therefore consider investigating the effect of previous eye tracking experience on gaze patterns.

In this study, participants were allowed to consume the coffee and sweets offered to them as a reward either before or after the eye tracking task. For future studies, the reward should either be restricted to being eaten after the test, or it should be noted if any of the food was consumed pre-test. Another uncertain factor is communication between test subjects, especially when recruiting groups of three or more, in which case the first subject to be tested may divulge information about the test to the other person(s) waiting in front of the testing room.

Due to the large influence of the left-right bias, it might be a worthwhile idea to explore ways of mitigating it, the most obvious solution being to prepare a parallel sequence of images where the positions of the AOIs are switched (this approach may however necessitate a larger number of participants to reduce the effect of interpersonal differences).

7 References

1. Unknown, *"La Dame à la licorne - La Vue"*. 14XX.
2. Unknown, *"La Dame à la licorne - À mon seul désir"*. 14XX.
3. Stephenson, N., *Cryptonomicon*. 1999: Avon Publications.
4. Wikipedia. *Sucht#Etymologie*. Wikipedia, The Free Encyclopedia 2010 [cited 2010 Nov 11th]; Available from: http://de.wikipedia.org/wiki/Sucht#Etymologie.
5. Rothemund, Y., et al., *Differential activation of the dorsal striatum by high-calorie visual food stimuli in obese individuals.* NeuroImage, 2007. **37**(2): p. 410-421.
6. Wang, G.-J., et al., *Similarity between obesity and drug addiction as assessed by neurofunctional imaging: A concept review.* Journal of addictive diseases, 2004. **23**(3): p. 15.
7. Grüsser, S.M., et al., *Stimulus-induced craving and startle potentiation in abstinent alcoholics and controls.* European Psychiatry, 2002. **17**(4): p. 188-193.
8. Lee, M. and R. Shafran, *Information processing biases in eating disorders.* Clinical Psychology Review, 2004. **24**(2): p. 215-238.
9. Nijs, I.M.T., et al., *Differences in attention to food and food intake between overweight/obese and normal-weight females under conditions of hunger and satiety.* Appetite, 2010. **54**(2): p. 243-254.
10. Piech, R.M., M.T. Pastorino, and D.H. Zald, *All I saw was the cake. Hunger effects on attentional capture by visual food cues.* Appetite, 2010. **54**(3): p. 579-582.
11. DeHouwer, J. and A. Moors, *How to define and examine the implicitness of implicit measures*, in *Implicit measures of attitudes: Procedures and controversies* 2007, Guilford Press. p. 179-194.
12. Steffens, M.C., *Is the Implicit Association Test Immune to Faking?* Experimental Psychology, 2004. **51**: p. 165-179.
13. Wallner, J.M., *Untersuchungen zur BMI-Abhängigkeit des Blickverhaltens von Frauen bei Lebensmitteln mit unterschiedlichem Kaloriengehalt mit Hilfe eines Tobii Eye Trackers*, in *H75 Department für Lebensmittelwissenschaften und -technologie*. 2009, University of Natural Resources and Applied Life Sciences, Vienna: Vienna.
14. Hepworth, R., et al., *Negative mood increases selective attention to food cues and subjective appetite.* Appetite, 2010. **54**(1): p. 134-142.
15. Habhab, S., J.P. Sheldon, and R.C. Loeb, *The relationship between stress, dietary restraint, and food preferences in women.* Appetite, 2009. **52**(2): p. 437-444.
16. *Scientific Research Brochure*. [cited 2010 Feb 16th]; Available from: http://www.tobii.com/archive/files/19055/Tobii+Scientific+Research+Brochure.pdf.aspx.
17. Wieser, M., et al., *Fear of negative evaluation and the hypervigilance-avoidance hypothesis: an eye-tracking study.* Journal of Neural Transmission, 2009. **116**(6): p. 717-723.
18. Clarke, A.H., *Vestibulo-oculomotor research and measurement technology for the space station era.* Brain Research Reviews, 1998. **28**(1-2): p. 173-184.
19. *"Market Research Brochure"* [cited 2010 Feb 16th]; Available from: http://www.tobii.com/archive/files/18890/Tobii_MR_Brochure_WEB.pdf.aspx.
20. Nielsen, J. *Eyetracking Methodology: 65 Guidelines for How to Conduct and Evaluate Usability Studies Using Eyetracking*. [cited 2010 Mar 1st]; Available from: http://www.useit.com/eyetracking/methodology/.
21. *Usability Research Brochure*. [cited 2010 Feb 16th]; Available from: http://www.tobii.com/archive/files/18997/Tobii+Usability+Brochure.pdf.aspx.

22. *SMI 6 D Eyetracking Flyer*. [cited 2010 Feb 16th]; Available from: http://www.smivision.com/fileadmin/user_upload/downloads/product_flyer/prod_smi_6D_tracking.pdf.
23. Kollenberg, T., Neumann, A., Schneider, D., Tews, T.-K., Dierker, A., Koesling, H., *The influence of head-mounted displays on head and eye movements during visual search*. 2009.
24. Klingner, J., *Measuring Cognitive Load During Visual Tasks by Combining Pupillometry and Eye Tracking*, in *Department of Computer Science*. 2010, Stanford University.
25. *SMI RED Flyer*. [cited 2010 Nov 16th]; Available from: http://www.smivision.com/fileadmin/user_upload/downloads/product_flyer/prod_smi_iviewx_red.pdf.
26. *Tobii TX300 Eye Tracker Brochure* 2010 [cited 2010 Nov 16th]; Tobii TX300 Eye Tracker For research of oculomotor functions and natural human behavior]. Available from: http://www.tobii.com/archive/files/21240/Tobii_Brochure_TX300_08112010_usENG_mini.pdf.aspx.
27. Gopal, I.S. and G.G. Haddad, *Automatic detection of eye movements in REM sleep using the electrooculogram.* Am J Physiol Regul Integr Comp Physiol, 1981. **241**(3): p. R217-221.
28. *An introduction to eye tracking and Tobii Eye Tracker*. 2010 [cited 2010 Mar 31st]; Available from: http://www.scribd.com/doc/25907389/Tobii-Eye-Tracking-An-introduction-to-eye-tracking-and-Tobii-Eye-Tracker.
29. Partala, T. and V. Surakka, *Pupil size variation as an indication of affective processing.* International Journal of Human-Computer Studies, 2003. **59**(1-2): p. 185-198.
30. Klingner, J. *The pupillometric precision of a remote video eye tracker*. 2010. Austin, Texas: ACM.
31. *Tobii Studio 1.X user manual*. 2008, Tobii Technology AB.
32. Finkelstein, E.A., et al., *Annual Medical Spending Attributable To Obesity: Payer-And Service-Specific Estimates.* Health Aff, 2009. **28**(5): p. w822-831.
33. Hoek, H.W. and D.v. Hoeken, *Review of the prevalence and incidence of eating disorders.* International Journal of Eating Disorders, 2003. **34**(4): p. 383-396.
34. Palmer, R., *Bulimia nervosa: 25 years on.* The British Journal of Psychiatry, 2004. **185**(6): p. 447-448.
35. Blinder, B.J., E.J. Cumella, and V.A. Sanathara, *Psychiatric Comorbidities of Female Inpatients With Eating Disorders.* Psychosom Med, 2006. **68**(3): p. 454-462.
36. Khazaal, Y., et al., *Cognitive behavioural therapy for weight gain associated with antipsychotic drugs.* Schizophrenia Research, 2007. **91**(1-3): p. 169-177.
37. Khazaal, Y., et al., *Long-term topiramate treatment of psychotropic drug-induced weight gain: a retrospective chart review.* General Hospital Psychiatry. **29**(5): p. 446-449.
38. McElroy, S.L., et al., *Topiramate in the Treatment of Binge Eating Disorder Associated With Obesity: A Randomized, Placebo-Controlled Trial.* Am J Psychiatry, 2003. **160**(2): p. 255-261.
39. Khazaal, Y. and D. Zullino, *Topiramate-induced weight loss is possibly due to the blockade of conditioned and automatic processes.* European Journal of Clinical Pharmacology, 2007. **63**(9): p. 891-892.
40. Vitale, R.M., et al., *Molecular modeling study for the binding of zonisamide and topiramate to the human mitochondrial carbonic anhydrase isoform VA.* Bioorganic & Medicinal Chemistry, 2007. **15**(12): p. 4152-4158.

41. Gadde, K.M., et al., *Zonisamide for Weight Loss in Obese Adults: A Randomized Controlled Trial.* JAMA, 2003. **289**(14): p. 1820-1825.
42. *Orexigen Therapeutics, Inc. Product Candidates: Empatic*. [cited 2010 Feb 24th]; Available from: http://www.orexigen.com/candidates/candidates_empatic.php.
43. Zernig, G., et al., *Subjective Effects of Slow-Release Bupropion versus Caffeine as Determined in a Quasi-Naturalistic Setting.* Pharmacology, 2004. **70**(4): p. 206-215.
44. Slemmer, J.E., B.R. Martin, and M.I. Damaj, *Bupropion Is a Nicotinic Antagonist.* Journal of Pharmacology and Experimental Therapeutics, 2000. **295**(1): p. 321-327.
45. Fryer, J.D. and R.J. Lukas, *Noncompetitive Functional Inhibition at Diverse, Human Nicotinic Acetylcholine Receptor Subtypes by Bupropion, Phencyclidine, and Ibogaine.* Journal of Pharmacology and Experimental Therapeutics, 1999. **288**(1): p. 88-92.
46. Tutka, P., et al., *Bupropion-induced convulsions: Preclinical evaluation of antiepileptic drugs.* Epilepsy Research. **64**(1-2): p. 13-22.
47. Grover, S. and P. Das, *Can bupropion unmask psychosis*. 2009. p. 53-54.
48. Harbin. *2D structure of neurotransmitter dopamine. Created with BKChem and Extensible SVG Optimiser*. 2008 [cited 2010 Mar 8th]; Available from: http://upload.wikimedia.org/wikipedia/commons/thumb/6/6c/Dopamine2.svg/200px-Dopamine2.svg.png.
49. Wyvell, C.L. and K.C. Berridge, *Incentive Sensitization by Previous Amphetamine Exposure: Increased Cue-Triggered "Wanting" for Sucrose Reward.* J. Neurosci., 2001. **21**(19): p. 7831-7840.
50. Beninger, R.J. and R. Miller, *Dopamine D1-like Receptors and Reward-related Incentive Learning.* Neuroscience & Biobehavioral Reviews, 1998. **22**(2): p. 335-345.
51. Sasikumar, T.K., et al., *Remote functionalization of SCH 39166: Discovery of potent and selective benzazepine dopamine D1 receptor antagonists.* Bioorganic & Medicinal Chemistry Letters, 2010. **20**(3): p. 832-835.
52. Astrup, A., et al., *Randomized Controlled Trials of the D1/D5 Antagonist Ecopipam for Weight Loss in Obese Subjects[ast].* Obesity, 2007. **15**(7): p. 1717-1731.
53. Cincotta, A.H., E. Tozzo, and P.W.D. Scislowski, *Bromocriptine/SKF38393 treatment ameliorates obesity and associated metabolic dysfunctions in obese (ob/ob) mice.* Life Sciences, 1997. **61**(10): p. 951-956.
54. Cooper, S.J., H.A. Al-Naser, and P.G. Clifton, *The anorectic effect of the selective dopamine D1-receptor agonist A-77636 determined by meal pattern analysis in free-feeding rats.* European Journal of Pharmacology, 2006. **532**(3): p. 253-257.
55. Volkow, N.D., et al., *Nonhedonic food motivation in humans involves dopamine in the dorsal striatum and methylphenidate amplifies this effect.* Synapse, 2002. **44**(3): p. 175-180.
56. Goldfield, G.S., C. Lorello, and E. Doucet, *Methylphenidate reduces energy intake and dietary fat intake in adults: a mechanism of reduced reinforcing value of food?* Am J Clin Nutr, 2007. **86**(2): p. 308-315.
57. www.cnn.com. *ADHD drug use for obesity raises ethical questions*. 2007 [cited 2010 Feb 17th]; Available from: http://edition.cnn.com/2007/HEALTH/03/21/vs.adderall/.
58. Astrup, A., et al., *Effect of tesofensine on bodyweight loss, body composition, and quality of life in obese patients: a randomised, double-blind, placebo-controlled trial.* The Lancet, 2008. **372**(9653): p. 1906-1913.
59. Davis, C., et al., *Dopamine Transporter Gene (DAT1) Associated with Appetite Suppression to Methylphenidate in a Case-Control Study of Binge Eating Disorder.* Neuropsychopharmacology, 2007. **32**(10): p. 2199-2206.
60. NEUROtiker. *Struktur von Serotonin (5-Hydroxytryptamin, 5-HT)*. 2007 [cited 2010 Mar 8th]; Available from:

http://upload.wikimedia.org/wikipedia/commons/thumb/0/04/Serotonin_(5-HT).svg/200px-Serotonin_(5-HT).svg.png.

61. Alex, K.D., et al., *Modulation of dopamine release by striatal 5-HT2C receptors.* Synapse, 2005. **55**(4): p. 242-251.
62. Stahl, S.M., L. Mignon, and J.M. Meyer, *Which comes first: atypical antipsychotic treatment or cardiometabolic risk?* Acta Psychiatrica Scandinavica, 2009. **119**(3): p. 171-179.
63. Sargent, P.A., et al., *5-HT2C receptor activation decreases appetite and body weight in obese subjects.* Psychopharmacology, 1997. **133**(3): p. 309-312.
64. Pissios, P. and E. Maratos-Flier, *More Than Satiety: Central Serotonin Signaling and Glucose Homeostasis.* 2007. **6**(5): p. 345-347.
65. Farooqi, I.S., et al., *Clinical Spectrum of Obesity and Mutations in the Melanocortin 4 Receptor Gene.* N Engl J Med, 2003. **348**(12): p. 1085-1095.
66. Leone, M., et al., *The serotonergic agent m-chlorophenylpiperazine induces migraine attacks: A controlled study.* Neurology, 2000. **55**(1): p. 136-139.
67. *Lorcaserin for Weight Loss*. [cited 2010 Feb 23rd]; Available from: http://www.arenapharm.com/wt/page/lho.html.
68. prnewswire.com. *FDA Issues Complete Response Letter for Lorcaserin New Drug Application*. 2010 [cited 2010 Oct 23rd]; Available from: http://www.prnewswire.com/news-releases/fda-issues-complete-response-letter-for-lorcaserin-new-drug-application-105586113.html.
69. Luque, C.A. and J.A. Rey, *The discovery and status of sibutramine as an anti-obesity drug.* European Journal of Pharmacology, 2002. **440**(2-3): p. 119-128.
70. *European Medicines Agency recommends suspension of marketing authorisations of Sibutramine*. 2010 [cited 2010 Feb 23rd]; Available from: http://www.ema.europa.eu/pdfs/human/referral/sibutramine/3940810en.pdf.
71. Jung, J., M. Hermanns-Clausen, and W. Weinmann, *Anorectic sibutramine detected in a Chinese herbal drug for weight loss.* Forensic Science International, 2006. **161**(2-3): p. 221-222.
72. Connolly, H.M., et al., *Valvular Heart Disease Associated with Fenfluramine-Phentermine.* N Engl J Med, 1997. **337**(9): p. 581-588.
73. Saul, S. *Fen-Phen case lawyers say they'll reject Wyeth offer*. New York Times 2005 [cited 2010 Feb 23rd]; Available from: http://query.nytimes.com/gst/fullpage.html?res=9505E7D6133AF934A25751C0A9639C8B63.
74. *Qnexa Obesity*. [cited 2010 Feb 23rd]; Available from: http://www.vivus.com/pipeline/qnexa-obesity.
75. Kaye, W., *Neurobiology of anorexia and bulimia nervosa.* Physiology & Behavior, 2008. **94**(1): p. 121-135.
76. David, R.R., J.S. Peter, and A.R. Catherine, *Estrogen–serotonin interactions: implications for affective regulation.* Biological psychiatry, 1998. **44**(9): p. 839-850.
77. FAIRBURN, et al., *Risk factors for bulimia nervosa : A community-based case-control study*. Vol. 54. 1997, Chicago, IL, USA: American Medical Association.
78. NEUROtiker. *Structure of gamma-aminobutyric acid (GABA)*. 2007 [cited 2010 Mar 8th]; Available from: http://upload.wikimedia.org/wikipedia/commons/thumb/4/4e/Gamma-Aminobutters%C3%A4ure_-_gamma-aminobutyric_acid.svg/200px-Gamma-Aminobutters%C3%A4ure_-_gamma-aminobutyric_acid.svg.png.
79. Duke, A., et al., *Enhanced sucrose pellet consumption induced by benzodiazepine-type drugs in squirrel monkeys: role of GABAA receptor subtypes.* Psychopharmacology, 2006. **187**(3): p. 321-330.

80. Timothy, I.M. and H.S. Michael, *Amnestic sleep-related eating disorder associated with zolpidem.* Sleep medicine, 2002. **3**(4): p. 323-327.
81. Choquette, A.C., et al., *GAD2 gene sequence variations are associated with eating behaviors and weight gain in women from the Quebec family study.* Physiology & Behavior, 2009. **98**(4): p. 505-510.
82. Cooper, S.J., et al., *Benzodiazepine receptor ligands and the consumption of a highly palatable diet in non-deprived male rats.* Psychopharmacology, 1985. **86**(3): p. 348-355.
83. Contó, M.B., J.G.B. de Carvalho, and M.A.C. Benedito, *Behavioral differences between subgroups of rats with high and low threshold to clonic convulsions induced by DMCM, a benzodiazepine inverse agonist.* Pharmacology Biochemistry and Behavior, 2005. **82**(3): p. 417-426.
84. Farooqi, S., *Treating obesity: Does antagonism of NPY fit the bill?* Cell Metabolism, 2006. **4**(4): p. 260-262.
85. Dryden, S., et al., *Increased neuropeptide Y secretion in the hypothalamic paraventricular nucleus of obese (fa/fa) Zucker rats.* Brain Research, 1995. **690**(2): p. 185-188.
86. Kaye, W.H., et al., *Altered Cerebrospinal Fluid Neuropeptide Y and Peptide YY Immunoreactivity in Anorexia and Bulimia Nervosa.* Arch Gen Psychiatry, 1990. **47**(6): p. 548-556.
87. Michel, M.C., et al., *XVI. International Union of Pharmacology Recommendations for the Nomenclature of Neuropeptide Y, Peptide YY, and Pancreatic Polypeptide Receptors.* Pharmacological Reviews, 1998. **50**(1): p. 143-150.
88. Erondu, N., et al., *Neuropeptide Y5 receptor antagonism does not induce clinically meaningful weight loss in overweight and obese adults.* Cell Metabolism, 2006. **4**(4): p. 275-282.
89. Degen, L., et al., *Effect of Peptide YY3-36 on Food Intake in Humans.* Gastroenterology, 2005. **129**(5): p. 1430-1436.
90. Gantz, I., et al., *Efficacy and Safety of Intranasal Peptide YY3-36 for Weight Reduction in Obese Adults.* J Clin Endocrinol Metab, 2007. **92**(5): p. 1754-1757.
91. Kamiji, M.M. and A. Inui, *Neuropeptide Y Receptor Selective Ligands in the Treatment of Obesity.* Endocr Rev, 2007. **28**(6): p. 664-684.
92. *Obinepitide*. [cited 2010 Feb 24th]; Available from: http://www.7tm.com/R-D/Metabolic_Disorders/Obinepitide.aspx.
93. Walker, M.W., et al., *The Novel Neuropeptide Y Y5 Receptor Antagonist Lu AA33810 [N-[[trans-4-[(4,5-Dihydro[1]benzothiepino[5,4-d]thiazol-2-yl)amino]cyclohexyl]methyl]-methanesulfonamide] Exerts Anxiolytic- and Antidepressant-Like Effects in Rat Models of Stress Sensitivity.* Journal of Pharmacology and Experimental Therapeutics, 2009. **328**(3): p. 900-911.
94. Kask, A., L. Rägo, and J. Harro, *Anxiogenic-like effect of the neuropeptide Y Y1 receptor antagonist BIBP3226: antagonism with diazepam.* European Journal of Pharmacology, 1996. **317**(2-3): p. R3-R4.
95. Yikrazuul. *Tetrahydrocannabinol; THC; Marinol*. 2010 [cited 2010 Mar 8th]; Available from: http://upload.wikimedia.org/wikipedia/commons/thumb/4/4c/Tetrahydrocannabinol.svg/200px-Tetrahydrocannabinol.svg.png.
96. Fvasoncellos. *Skeletal formula of anandamide. Created using ACD/ChemSketch 10.0 and Inkscape.* 2007 [cited 2010 Mar 8th]; Available from: http://upload.wikimedia.org/wikipedia/commons/thumb/b/b7/Anandamide_skeletal.svg/200px-Anandamide_skeletal.svg.png.
97. Richard, H., *Cannabinoid-Rezeptor1 und Essstörungen*, in *Medizinischen Fakultät*. 2009, Friedrich-Alexander-Universität: Erlangen-Nürnberg.

98. Monteleone, P., et al., *Blood Levels of the Endocannabinoid Anandamide are Increased in Anorexia Nervosa and in Binge-Eating Disorder, but not in Bulimia Nervosa.* Neuropsychopharmacology, 2005. **30**(6): p. 1216-1221.
99. Arias Horcajadas, F., *Cannabinoids in Eating Disorders and Obesity.* Molecular Neurobiology, 2007. **36**(1): p. 113-128.
100. Arnone, M., et al., *Selective inhibition of sucrose and ethanol intake by SR 141716, an antagonist of central cannabinoid (CB1) receptors.* Psychopharmacology, 1997. **132**(1): p. 104-106.
101. *Food and Drug Administration Endocrinologic and Metabolic Advisory (June 13, 2007) Briefing information, NDA 21-888 ZIMULTI (rimonabant)-Sanofi Aventis*. 2007 [cited 2010 Feb 24th]; Available from: http://www.fda.gov/ohrms/dockets/ac/07/briefing/2007-4306b1-fda-backgrounder.pdf.
102. Cravatt, B.F., et al., *Supersensitivity to anandamide and enhanced endogenous cannabinoid signaling in mice lacking fatty acid amide hydrolase.* Proceedings of the National Academy of Sciences of the United States of America, 2001. **98**(16): p. 9371-9376.
103. Mechoulam, R. and D.G. Deutsch, *Toward an anandamide transporter.* Proceedings of the National Academy of Sciences of the United States of America, 2005. **102**(49): p. 17541-17542.
104. Le Foll, B., D. Gorelick, and S. Goldberg, *The future of endocannabinoid-oriented clinical research after CB1 antagonists.* Psychopharmacology, 2009. **205**(1): p. 171-174.
105. Colantuoni, C., et al., *Excessive sugar intake alters binding to dopamine and mu-opioid receptors in the brain.* NeuroReport, 2001. **12**(16): p. 3549-3552.
106. Colantuoni, C., et al., *Evidence That Intermittent, Excessive Sugar Intake Causes Endogenous Opioid Dependence.* Obesity, 2002. **10**(6): p. 478-488.
107. Avena, N.M., P. Rada, and B.G. Hoebel, *Evidence for sugar addiction: Behavioral and neurochemical effects of intermittent, excessive sugar intake.* Neuroscience & Biobehavioral Reviews, 2008. **32**(1): p. 20-39.
108. Fvasoncellos. *Skeletal formula of naltrexone. Created with ACD/ChemSketch 10.0, Inkscape and vim.* 2008 [cited 2010 Mar 8th]; Available from: http://upload.wikimedia.org/wikipedia/commons/thumb/4/4d/Naltrexone_skeletal.svg/200px-Naltrexone_skeletal.svg.png.
109. Sinclair, J.D., *Evidence about the use of naltrexone and for different ways of using it in the treatment of alcoholism.* Alcohol Alcohol., 2001. **36**(1): p. 2-10.
110. Schmitz, J.M., et al., *Naltrexone and relapse prevention treatment for cocaine-dependent patients.* Addictive Behaviors. **26**(2): p. 167-180.
111. MARRAZZI, et al., *Binge eating disorder : response to naltrexone*. Vol. 19. 1995, Basingstoke, ROYAUME-UNI: Nature Publishing.
112. Jonas, J.M. and M.S. Gold, *The use of opiate antagonists in treating bulimia: A study of low-dose versus high-dose naltrexone.* Psychiatry Research, 1988. **24**(2): p. 195-199.
113. Schmahl, C., et al., *Behandlung von dissoziativen Symptomen bei Borderline-Persönlichkeitsstörungen mit Naltrexon.* Der Nervenarzt, 1999. **70**(3): p. 262-264.
114. *Contrave Poster*. [cited 2010 March 1st]; Available from: http://phx.corporate-ir.net/External.File?item=UGFyZW50SUQ9NTM0OHxDaGlsZElEPS0xfFR5cGU9Mw==&t=1.
115. *Orexigen Therapeutics, Inc. Product Candidates: Contrave*. [cited 2010 Feb 28th]; Available from: http://www.orexigen.com/candidates/candidates_contrave.php.
116. Kaye, W., K. Gendall, and M. Strober, *Serotonin neuronal function and selective serotonin reuptake inhibitor treatment in anorexia and bulimia nervosa.* Biological psychiatry, 1998. **44**(9): p. 825-838.

117. Fettrechner.de. 2010 [cited 2010 Nov 1st]; Available from: www.fettrechner.de.
118. Database, F. 2010 [cited 2010 Nov 1st]; Available from: www.fddb.info.
119. McDonalds.at. 2009 [cited 2010 Nov 1st]; Available from: www.mcdonalds.at.
120. Burgerking.at. 2010 [cited 2010 Nov 1st]; Available from: www.burgerking.at.
121. Elmadfa, I., *Österreichischer Ernährungsbericht*. 2003, Institut für Ernährungswissenschaften, Universität Wien.
122. Biggs, M.L., et al., *Association Between Adiposity in Midlife and Older Age and Risk of Diabetes in Older Adults.* JAMA, 2010. **303**(24): p. 2504-2512.
123. Dragan, A. and N. Akhtar-Danesh, *Relation between body mass index and depression: a structural equation modeling approach.* BMC Medical Research Methodology, 2007. **7**(1): p. 17.
124. Drewnowski, A., et al., *Food preferences in human obesity: Carbohydrates versus fats.* Appetite, 1992. **18**(3): p. 207-221.
125. Kukkonen, S. (2005) *Exploring Eye Tracking in Design Evaluation*.
126. Nielsen, J. *Horizontal Attention Leans Left*. 2010 [cited 2010 Oct 31st]; Available from: http://www.useit.com/alertbox/horizontal-attention.html.
127. Nielsen, J. *Scrolling and Attention*. 2010 [cited 2010 Oct 31st]; Available from: http://www.useit.com/alertbox/scrolling-attention.html.
128. Al-Wabil, A. and H. Al-Khalifa, *A Framework for Integrating Usability Evaluations Methods: The Mawhiba Web Portal Case Study*. 2009, College of Computer and Information Sciences, King Saud University.
129. Haindl, M., *Eye Tracking-Analysen von Lebensmitteln unterschiedlicher visueller Attraktivität*, in *Department für Lebensmittelwissenschaften und -technologie*. 2010, University of Natural Ressources and Applied Life Sciences: Vienna.