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# Decision Biases in Food Recommendation Systems

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# Abstract

Food recommender systems have become increasingly popular in recent years, aiding users in discovering new restaurants, recipes, and dietary choices. However, these systems are not immune to decision biases that can impact the quality and diversity of recommendations. Since Food Recommender Systems can impact people's health, these biases are often used to nudge people to choose healthier options. Among other decision biases, the Decoy effect, Position effect, and Explanations are mentioned very often. In this paper, we empirically test all the mentioned effects and the combinations of two or three in the Food Recommender Systems domain.

**Keywords:** Food Recommender Systems, Decoy effect, Position effect, Explanations



# Kurzfassung

Systeme zur Empfehlung von Lebensmitteln sind in den letzten Jahren immer beliebter geworden und helfen den Nutzern bei der Entdeckung neuer Restaurants, Rezepte und Ernährungsentscheidungen. Diese Systeme sind jedoch nicht vor Entscheidungsfehlern gefeit, die sich auf die Qualität und Vielfalt der Empfehlungen auswirken können. Da Systeme zur Empfehlung von Lebensmitteln einen Einfluss auf die Gesundheit der Menschen haben können, werden diese Verzerrungen oft genutzt, um die Menschen dazu zu bewegen, gesündere Optionen zu wählen. Unter anderen Entscheidungsfehlern werden der Decoy-Effekt, der Positionseffekt und Erklärungen sehr häufig genannt. In diesem Beitrag testen wir empirisch alle genannten Effekte und die Kombinationen aus zwei oder drei Effekten im Bereich der Lebensmittelempfehlungssysteme.

**Schlagworte:** Food Recommender Systems, Decoy-Effekt, Positionseffekt, Erklärungen





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# 1 Introduction

## 1.1 Motivation

Individuals who are occasionally ill experience moments of physical weakness. For example, women who have recently given birth need to eat to regulate their bodies because they are fragile, and people who have recently undergone surgery also need the proper nourishment. On every level, their bodies are undernourished. Their bodies need nutrients from food and drugs to stimulate their recovery. There is little advice on selecting healthy foods among the materials or references currently available for food recommendations. There is some information. However, it is only a list of instructions in plain text. Unhealthy individuals are also impacted by the difficulties of having few references for the ideal foods. Most references come from printed, static sources like books and newspapers. Food recommendation systems are one of the clever ways to help people manage and organize their dietary consumption. [1]

The idea of "nudging" was developed by Thaler and Sunstein in [2], who defined it as "any aspects of the choice architecture that alters people's behavior predictably without forbidding any options or significantly changing their economic incentives." Humans can make better decisions with the help of nudges, without having their freedom or options reduced. Nudges uphold people's freedom to select any alternative, but they highlight a certain option that is superior in a certain sense. People may be able to choose better eating options with nudging. [3] 39.6% of the studies on nudges, according to Hummel and Maedche in [4], concentrate on the health context.

In contrast to an offline (real world) setting, while developing a nudge in a digital context, one must examine how activities, interactions, and influencing variables may affect individual differences. Because humans rely heavily on heuristics and their accompanying cognitive (decision) biases, nudges attempt to address these biases by either promoting or discouraging them (Weinmann et al., 2016). Nudges, when applied to an online setting, attempt to alter the decision environment such that human behavior is altered, presumably for the better. [5]

### 1.2 Our contribution

This thesis will analyze the influence of three different decision biases. There is already a significant amount of research on the impact of the Decoy Effect, Position Effect, or Explanations as biases in Food Recommendation Systems. After presenting each important component in this thesis, we also summarized this research. To test their influence on users, we have created the user study in a web application where users can choose from different food variations in different scenarios. These scenarios include decision biases or even combinations of those, allowing us to test the impact of combinations on users. The results of the user study are discussed and evaluated in detail so the influence of every effect and every combination can be presented along with the connection of this influence with other factors that are part of everyday food choice.

### 1.3 Outline of the thesis

In Chapter 2, Recommender Systems and their different variants, along with decision biases, are introduced. Following is the description of Food Recommender Systems, and lastly, a state-of-the-art analysis is given.

Chapter 3 presents the user study, including the problem statement and implementation.

In Chapter 4, the results of the user study are presented.

Finally, in Chapter 5, the whole thesis is summarized with a special preview of possible future work that could follow this thesis.



## 2 Background and Related Work

In this chapter, Recommender Systems and their different techniques are presented with three different decision biases that can subconsciously affect users' choices. Since the area of interest is Food Recommendation and biasing the user to choose healthy food, this chapter also focuses on related research in Food Recommender Systems.

### 2.1 Recommender Systems

Unlike customers who shop in physical stores, online shoppers do not receive assistance from human sales experts. In those situations, recommender systems—which function similarly to sales experts—can be helpful. They assist in tracking products that meet the user's prerequisites. [6] Recommender systems help users and customers make decisions in various decision-making situations [7]. When it comes to online selling environments, users can find the most appropriate candidates from a selection of items with the help of it. [8] The enormous amount of information overwhelm that comes with using the Internet has made it harder to find and retrieve meaningful information. A recommender system generates suggestions for novel items based on an estimation of user preferences for unassessed items. There has been a massive increase in the creation of novel recommendation techniques and their widespread application in various domains that is further to the advantages of recommender systems. The most prominent technique family among them is collaborative filtering (CF). [9]

### 2.1.1 Collaborative filtering (CF)

CF uses recorded user ratings to find comparable users and suggests things these peers have previously enjoyed. When it comes to areas concerning the consumer's taste where people can experience and judge a wide range of things, like music, films, or books, CF is particularly helpful. Collaborative filtering imitates word-of-mouth advertising, in which friends' recommendations and benchmarking data influence purchasing decisions. [9]

The recommendation engine that Amazon uses is one instance of collaborative filtering in action. Amazon's recommender system analyzes the purchase history and browsing behavior of millions of users to generate personalized product recommendations. Collaborative filtering finds patterns in the likes and dislikes of users and recommends products that people with similar tastes have liked. Shopping cart recommendations, as illustrated in Figure 2, offer recommendations for products to customers based on the items they currently have in their basket. The way it works is similar to the impulsive decisions people make in grocery store checkout lines, but with personalised impulse purchases on Amazon. [10]



Figure 2.1: Amazon shopping cart recommendations [10]

In more complex industries with products that involve the consumer in taking time and trouble before deciding on a purchase, like electronic consumer goods, only a small number of user evaluations can be obtained, leaving the CF tactics useless. Accordingly, various elicitation techniques, like feature- or needs-oriented conversational dialogues, are used by knowledge-based recommendation (KBR) tactics to determine customer preferences.

### 2.1.2 Knowledge-based recommender systems(KBR)

The second version of the recommender system combines user and item data to make recommendations which items would be best for the user. Unlike other recommender systems, they do not rely on enormous amounts of statistical data on specific rated objects or users. It is proven that the knowledge component of these systems does not need to be unreasonably broad, as we only require enough knowledge to assess objects as related. Furthermore, knowledge-based recommender systems assist users in exploring and thereby identifying an information space. Users are essential to the knowledge discovery process, developing their information requirements as they engage with the system. One requires a general understanding of the collection of things and an informal understanding of one's goals; the system is aware of the domain's tradeoffs, category borders, and useful search algorithms. [11]

As of 2018, Spotify [12], one of the market leaders in the online music streaming space, offers suggestions via a variety of its platform and applications' features. For instance, Johnson (2014) cites them as supporting discovery through tailored suggestions. They also create weekly listeners' personalised playlists (also referred to as "mix tapes") and provide a "release radar" that helps users discover new music that they might enjoy. [13]

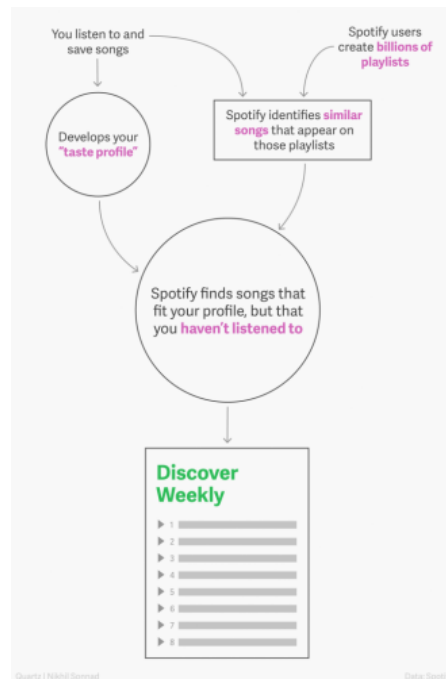


Figure 2.2: The process of creating a weekly personalized playlist for users [14]

### 2.1.3 Content-based recommender systems (CB)

Learning customized profiles from examples (content-based recommendations) enables a system to characterize each user individually without matching their likes to others. Items are recommended based on facts regarding the item rather than other users' preferences. This also opens the door to offering explanations that explain the content elements that prompted an item to be recommended, thus giving readers confidence in the system's suggestions and insight into their preferences. [15]

For the purpose of creating client profiles as well as content representations, i.e., item profiles, content-based separation techniques frequently utilize content extraction and characterization systems. These methods have a few flaws, such as the confusion between client profile items and profile keywords that results in poor execution. Frameworks for content-based recommendations provide products with similar content to those that the customer has lately appreciated. [16] In different application fields, many content-based recommender systems are in use. Using text classification algorithms to learn from movie synopses gathered from the Internet Movie Database (IMDB [17]), INTIMATE [18] suggests movies. The user must rank a minimum number of movies into one of six categories—terrible, bad, below average, above average, good, and excellent—in order to get suggestions. [19]

### 2.1.4 Hybrid recommender systems (HRS)

The combination of the methods mentioned previously forms the foundation of HRS. [20] Hybrid recommender systems combine two or more recommendation algorithms to reduce the drawbacks of each and increase performance. Often, collaborative filtering is used in conjunction with another strategy to prevent the ramp-up issue. [21]

From a technical standpoint, recommendation systems can be thought of as an estimation model that evaluates the likelihood that a user will enjoy a particular product. Nevertheless, this limited machine-learning approach on product suggestion just slightly matches the context of internet customer help with making choices. [22] 2.3 shows the general layout of the YouTube recommendation system. The system uses two neural networks: one for hierarchy arrangement and one for generating possibilities. From a large corpus of videos, the possibilities generation network receives hundreds of films as input. The purpose of these possibilities is to be highly specific and widely applicable to the user. This network only offers broad personalization through collaborative filtering. Similarity between customers is expressed in terms of coarse data, including search terms, watching session code, and demographic data. To fulfil this task, the ranking (hierarchy arrangement) network uses a variety of features that characterise both the viewer and the video to assign a grade (rank) to each video based on a predetermined goal function. The user is presented with the top graded videos arranged by grade. In addition to selecting videos for recommendations from a vast collection (countless videos), the dual-phase recommendation method guarantees that the limited number of movies that appear on the device are significant and engaging for the user. [23]

The Netflix Recommender System (NRS) primarily relies on machine learning to suggest content. It does this by combining collaborative filtering algorithms with content-based filtering. A user's prior interactions with the platform—such as their watching behavior or patterns, or browsing tendencies, and so forth—are the only factors that influence content-based filtering. The aforementioned data are merged with additional extensive and complex datasets that encompass details from the film and television offerings of Netflix, such as films, performers, filmmakers, categories, and year of publication, in order to generate suggestions and customise a user's encounter (Wasko and Meehan, 2020). Previously, the collaborative filtering recommendations made by the NRS were limited to data obtained from users within a specific country or region (Stenovc, 2016). According to Wasko and Meehan (2020), recommendations are currently based on the preferences for watching of users worldwide, and users are methodically classified into more than 2000 global "taste communities." Another source of Netflix's competitive advantage is the total amount of detail in the data it

collects, which the NRS transforms, groups, examines, and applies to produce recommendations. A "rich taxonomy of 200 different story data points" has been individually assigned to each movie or television show on Netflix by human specialists (Sundeeep, 2019). These tale characteristics range from the degree of romance, gore, and conclusiveness of the storyline to the moral standing of the characters. After being tagged, information is algorithmically arranged into the proper "thematic containers," which include genres and extremely specialized alt genres (Gomez-Urbe and Hunt, 2015). [24]

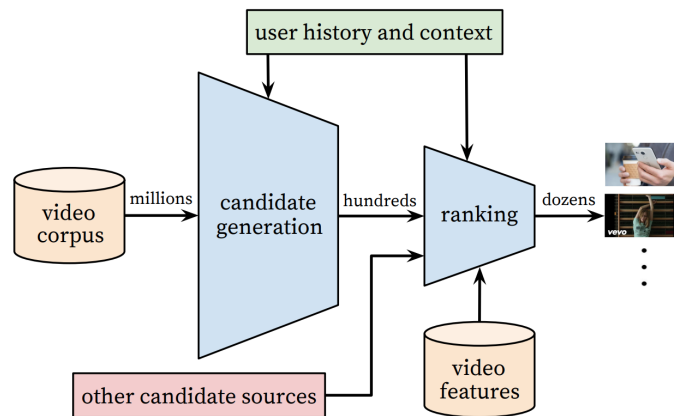


Figure 2.3: YouTube recommender system [23]

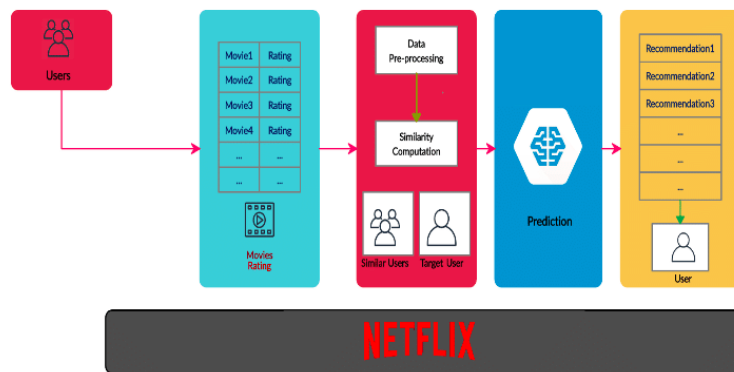


Figure 2.4: Netflix recommender system [25]

### 2.1.5 Other recommender systems

Apart from these, there are some other Recommender Systems that appear in some sources. Here we will present some of them.

#### **Demographic-based recommender systems (DRS)**

Recommendations are generated by means of demographic-based filtering, which takes into account user demographic characteristics like age, gender, whereabouts, and employment status. If the user profile consists of a list of attributes gleaned from the specifications of previously favoured products, then we have a content-based recommender system. We have a DRS, though, if their profile has a set of characteristics that identify the person's demographic segment. [26]

#### **Context-aware recommender systems**

To provide recommendations that are suitable for the given scenario, context-aware recommender systems make use of information about the environment, which might involve time, location, or weather. When choosing a vacation package, for instance, time information can be helpful. Additionally, a lot of people own mobile phones or tablets, and the recommender system can retrieve data from those devices, like time and location, to help it understand the setting. This is why mobile recommender systems are becoming really popular. This problem opens up a wider range of data on user behaviour in different scenarios, as a recommender system that is more aware of the environment may yield better results. For example, if a music recommender takes into account the listener's emotional state, their sphere of activity, and music they listen to while driving or reading, it can be more precise. [27]



### Knowledge graph-based recommender systems

Knowledge graph(KG)-based recommender systems utilize structured knowledge graphs that represent relationships between items, users, and attributes to make recommendations. Additionally, personal user information may be integrated into the KG, improving the accuracy of capturing user preferences and connections between users and objects. A KG-based suggestion is shown in Figure 1, suggesting to Bob that he watch the films "Avatar" and "Blood Diamond." Audience, films, performers, creators, and classifications are some of the entities that make up this KG. Interactions between entities include friendship, acting, directing, belonging, and interaction. Recommendation precision is enhanced by the KG's extensive underlying relational network connecting users and films. Another benefit of KG-based recommender systems is the clarification of recommendation outcomes. In the same example, Bob might be recommended these two films if one were to trace the associated user-item connections. For example, one justification for recommending "Avatar" is that it is in [28], DBpedia [29], YAGO [30], and Google's Knowledge Graph [31] have recently been suggested, making it easier to develop KGs for recommendations.

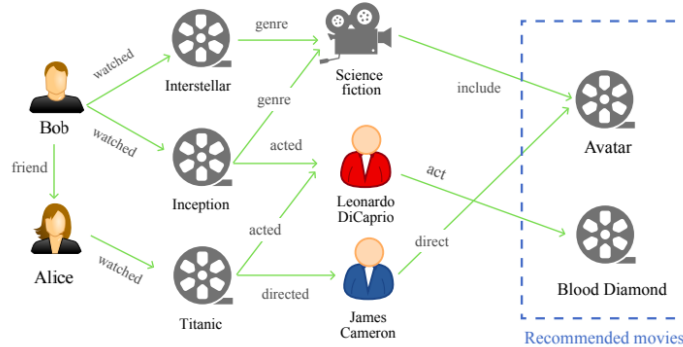


Figure 2.5: Knowledge graph-based recommender system [32]

## 2.2 How We Think

The way the human brain functions is a bit mysterious. How is it that we can be so clever at certain things yet so stupid at others? Beethoven's amazing Ninth Symphony was written when he was deaf, yet we wouldn't be surprised in the least if we heard that he frequently lost his house keys. How are individuals able to be so intelligent and yet so simple-minded? Many psychologists and neuroscientists have come to an agreement on a theory of how the brain works that explains these seeming discrepancies. The approach makes a contrast between two modes of thought: instinctive and intuitive thinking, and reflective and reasoned thinking. First is the Automatic System; second is the Reflective System. The Automatic System appears to be quick and natural, but it doesn't require the kind of thinking that we typically associate with it. When you giggle at a cute dog, move when a ball is suddenly thrown at you, or get nervous during aeroplane turbulence, your automatic system is activated. According to brain researchers, the Automatic System's functions are connected to the earliest regions of the brain—regions that humans and lizards (as well as 2 puppies) share. Individuals usually find it difficult to use their Reflective Systems to speak in a language other than their native tongue, and they usually speak it naturally. Being truly bilingual is defined as using the Automatic System to speak two languages. Expert athletes and chess players possess highly developed intuitions; their Automatic Systems allow them to analyse complicated situations rapidly and respond with remarkable accuracy and velocity. To put it all into perspective, your Automatic System is your automatic reaction, and your Reflective System is your consciously generated thought. Although gut instincts are frequently accurate, we frequently make blunders because we place too much trust in our Automatic System. [33]

Automatic System	Reflective System
Uncontrolled	Controlled
Effortless	Effortful
Associative	Deductive
Fast	Slow
Unconscious	Self-aware
Skilled	Rule-following

Figure 2.6: Two cognitive systems [33]

### 2.2.1 Libertarian paternalism

The idea of paternalism is showcased in [33] and arises from the belief that it's justifiable for decision influencers to aim for behavioral adjustments that promote the extension, betterment, and enrichment of individuals' lives. In essence, intentional efforts by government and corporate entities to guide people's decisions towards enhancing their well-being are endorsed. A protocol is labeled "paternalistic" when it endeavors to steer decisions in a manner that decision-makers themselves believe will advance their own circumstances. People frequently make poor decisions—decisions they would not have made if they had been fully attentive, fully informed, fully cognitively capable, and fully self-controlled—by drawing on some well-established social science data. Because options are not severely restricted, fenced off, or burdened, libertarian paternalism is a comparatively light, gentle, and non-intrusive sort of paternalism. Libertarian paternalists will not compel individuals to do anything against their will, including making life difficult for them if they choose to smoke cigarettes, consume excessive amounts of sweets, select an inadequate health insurance plan, or neglect to prepare for retirement. But the approach that authors support is indeed paternalistic, since both public and private decision influencers are trying to do more than just observe or implement people's pre-determined decisions. Instead, they are deliberately trying to influence others in ways that will improve their lives. They nudge.

Libertarian paternalists contend that there are several strategies to enhance peoples' health. Social influences certainly could be at play here: more people would follow suit if they perceive that more people are becoming more physically active or eating healthier food. As it is shown, knowing obese people raises one's chances of getting obese, and losing weight may also spread. The significance of framing cannot be emphasised: Individuals who are aware of a heightened risk of developing skin and breast cancer due to self-examination are more inclined to conduct the examinations compared to those who are informed of a reduced risk. As crucial decision makers, doctors could improve people's lives and health considerably more if they had a deeper understanding of human thought processes. [33]

### 2.2.2 Nudges

Nudges are private or public efforts that guide individuals in certain directions while simultaneously allowing them to pursue their interests (Thaler and Sunstein 2008; Thaler 2015). Similar to warnings, nudges fulfill the role of serving as reminders, gently directing individuals' attention or actions toward certain choices or behaviors. Ebeling and Lotz (2015) highlighted that the initial act of enrolling participants automatically in a program and the functionality of a GPS device both function as nudges. For an action to fall under the classification of a nudge, it must avoid implementing significant material rewards or penalties, distinctly differing from mechanisms such as taxation, subsidies, or imprisonment terms. The essence of a "nudge" lies in its preservation of individuals' freedom to choose, setting it apart as a strategy designed to gently guide decisions rather than coercively direct them. [34]

The primary argument advocating the ethical validity of nudges revolves around their potential to elevate individuals' subjective well-being. Thaler and Sunstein posit that nudges aim to influence decisions in a manner that leaves the decision-makers feeling improved according to their own judgments (Thaler & Sunstein, 2008, p. 5). They contend that nudges contribute to personal welfare by steering choices toward what individuals would likely opt for if their decisions weren't subject to mental biases, constrained self-regulation, or limitations in time, knowledge, and mental capacities. Based on these premises, Thaler and Sunstein propose that legislators intervene in people's decision-making processes to guide them toward choices aligning with their unbiased decision-making selves. [35] While rules of thumb are valuable tools, their application can inadvertently introduce systemic biases. The conception of human thought processes has evolved notably following the pivotal insights introduced decades ago by psychologists Amos Tversky and Daniel Kahneman (1974). Initially identifying heuristics such as anchoring, availability, and representativeness, these psychologists also highlighted the accompanying biases associated with each heuristic. Referred to as the "heuristics and biases" paradigm, this research program has recently revealed that these heuristics and biases arise from the interaction between the Automatic System and the Reflective System, altering psychologists' and, subsequently, economists' understanding of human judgment. [33]

## 2.3 Decision biases

According to Kahneman's (2003) observations, human decision-making frequently deviates from perfect rationality and ignores a sizable amount of accessible data. [36] The notion of limited rationality is first introduced by Simon (1959), who points out that human decision processes are limited by time constraints, limited computational capacity, and a propensity to avoid comprehensive processing, which results in inaccurate assessments of product utility. [22]

Users' preferences are not fixed when they interact with recommender systems; instead, they develop and shift over time. [37] In this situation, decision-makers' use of mental shortcuts, or heuristics, in conjunction with particular cognitive distortions leads to a variety of biases that affect their attitudes and methods for solving problems. [38]

The underlying algorithms and data may be unjust and prejudiced towards a specific community or group of people, leading to incorrect findings and decisions. For example, when employing COMPAS [39], a tool American courts use to predict the risk that a person will commit another crime, African-American criminals are more likely to have higher false positive rates. AI systems built on medical and usage data predominantly gathered from men may overstate the risk of heart attack experienced by women, exacerbating the gender disparity in health. Similar difficulties occur with AI-assisted retrieval algorithms that power Web search engines, as they may detect biases from data sources, algorithm authors, and customers "in the manner a child repeats the poor conduct of his parents." [40] In the literature, biases pertaining to cognition, decision-making, and memory have been found to number over 100. New biases are constantly being discovered and defined by researchers in cognitive and social psychology. [41] In this section, we will present some of them.

### 2.3.1 Anchoring

Let's say we are requested to determine Frankfurt's population estimate. How should we approach estimating? We could begin with what we do know, namely that there are approximately three million inhabitants living in Berlin. Frankfurt is a significant municipality, but it's unquestionably not as big as Berlin; perhaps it's about one-third the size, or about a million people. You might want to ask another person in Ulm, for the same estimation. Although they are unsure of the answer as well, they make a reasonable assumption based on the knowledge that Frankfurt has a population higher than that of Ulm, which is approximately 130,000. We call this "anchoring and adjustment." Starting with an anchor—a known number, for example—you tailor your approach based on what feels right to you. Everything is going well so far. As a consequence of insufficient corrections, bias arises. Extensive experiments show that people in Berlin have a tendency to predict higher (which is based on their high value anchor) in problems similar to this example, while people in Ulm are most likely to presume lower (relying on their relatively low anchor). In Frankfurt, there are about 750,000 residents. [33]

### 2.3.2 Availability

Are severe weather, nuclear energy, terrorist attacks, outbreaks of mad cow disease, wild animal attacks, or influenza scares worth having? And how careful should you be to steer clear of the dangers connected to each? What steps specifically should you take to prepare for the risks you encounter on a daily basis? The availability intuition is what most people use when responding to questions of this nature. They measure the likelihood of hazards by finding out how quickly instances come to mind. If people can quickly recall specific instances, they are much more likely to experience fear and anxiety. A risk that is well-known, like the acts of violence that followed 9/11, will be taken more seriously than an issue that is less well-known, like tanning or warmer summers. Relevance and reachability are both crucial and connected to availability. In comparison to reading about an influenza, you are tend to think it is likely if you have personally experienced one. Another heuristic is called representativeness, which is an odd word. Think of it as the intuition for similarity. People answer questions about how likely it is that A falls into the B classification by comparing A to their perception or perceptions of B, or how "representative" A is of B. In daily life, a heuristic can result in significant pattern misinterpretations. People expect the outcome of a line of heads and tails to be a metaphor of what they consider unknown when events, like a flip of a coin, happen by chance. Sadly, most people have incorrect ideas about what unpredictable patterns look like. They often notice patterns in the results of accidental events that they take to be very significant, but are actually just the product of chance. [33]

### 2.3.3 Framing effect

Different emotions can be evoked by the same information presented in different ways. It is more consoling to hear that "the 90% of patients survive one month after the procedure " as opposed to "fatalities of patients in the first month after the procedure is 10%." Comparably, juices with the label "90% sugar-free" look more attractive than those with the label "10% sugar." The equivalence of the various formulations is obvious, but most people only perceive one version, and what she sees is all there is. In many countries, an individual's driver's license includes a provision for organ donation in the event of an accident. Another instance where one frame plainly outperforms the other is the phrasing of that instruction. Few would disagree that the decision to give one's organs is unimportant, but there is significant evidence that most people make their decision haphazardly. A study of the rates of organ donation in European countries finds remarkable disparities between neighboring and culturally similar countries. According to a 2003 report, the percentage of organ donation in Austria was close to 100%, but just 12% in Germany, 86% in Sweden, and 4% in Denmark. These significant discrepancies are the result of a framing effect generated by the format of the important question. Individuals who do not desire to give must tick an appropriate box on the opt-out form in the high-donation nations. They are not considered willing contributors unless they do this basic action. To become a donor in the low-contribution nations, you must tick a box. That's all there is to it. The identification of the default choice that will be adopted without having to tick a box is the strongest single predictor of whether or not people would donate their organs. [42]

### 2.3.4 Sunk-Cost Fallacy

The decision to keep investing in a losing account when better choices are available is referred to as the sunk-cost fallacy. Both major and minor judgments may exhibit this costly error in reasoning. A sunk-cost error is entering a snowstorm after purchasing tickets. Consider a firm that has already invested \$60 million in a project. The expected profits have decreased since the project's inception, and it is currently behind schedule. It will take an additional \$70 million investment to give the endeavor a chance. The same money may also be used to fund a new initiative with a better chance of success. What will the business do? All too frequently, a firm suffering from concealed expenditures would rather drive into the storm, pouring good money after bad, than face the humiliation of shutting a costly failure's account. [42]

### 2.3.5 Hindsight Bias

Because of your incapacity to reconstruct former beliefs, you will invariably underestimate the amount to which past occurrences startled you. When he was a student in Jerusalem, Baruch Fischhoff first established the "I-knew-it-all-along" effect, often known as hindsight bias. Fischhoff performed a poll before President Richard Nixon's 1972 visit to China and Russia. The respondents assessed the probability of fifteen of Nixon's diplomatic endeavors. Would Mao Zedong be willing to meet with Nixon? Could the United States offer China diplomatic recognition? Could the US and the Soviet Union agree on anything major after decades of hostility? After Nixon returned from his trip, Fischhoff and Beyth asked the same respondents to recall the likelihood they had assigned to each of the fifteen possible outcomes. The outcomes were unmistakable. If an incident did occur, people overestimated the chance that they had previously attributed to it. If the hypothetical occurrence had not occurred, the participants incorrectly remembered that they had always thought it unlikely. Further trials revealed that people were compelled to exaggerate the accuracy of their own forecasts as well as those of others. [42]



### 2.3.6 Bandwagon Effect

The bandwagon effect is defined by Leibenstein (1950, p. 189) as “the extent to which the demand for a commodity is increased due to the fact that others are also consuming the same commodity.”. Bandwagon consumption is the term used to describe the practise of consumers purchasing particular luxury goods just because they are fashionable, particularly among well-known individuals, actors, and other celebrities. Due to their representation of success, fame and status in important social groups, these objects guarantee social acceptance. How susceptible a person is to social compliance dictates how closely reliant self and the influence of the crowd are related. Customers that exhibit dependent behaviour and a strong tendency to give in to aspirational group expectations make an effort to obtain items that are well-liked by members of the reference group. Significant correlations were discovered by Tsai, Yang, and Liu (2013) between this influence, a consumer’s need for uniqueness, and their exposure to peer pressure. [43]

### 2.3.7 Status Quo Bias

A fundamental component of the model of rational choices under conditions of certainty or uncertainty is that a person’s option selection is influenced only by characteristics of the options which are related to preference. Therefore, the order in which the alternatives are displayed or the symbols they carry shouldn’t have an impact on the person’s choice. Naturally, when faced with decisions in the real world, options usually have strong names attached to them. In fact, the status quo refers to the fact that there is almost always a choice to do nothing or stick with one’s current course of action or previous choice. Those making decisions often choose the status quo option when presented with new options. Examples of this include adhering to established company policy, re-electing the current government for an additional term, buying the goods from same companies, or continuing in the same role as before. People may uphold the status quo due to practicality, stagnation or routine, corporate or societal norms or tradition, fear or built-in conservatism, or straightforward justification. It’s possible that they made their prior decision known to those around them and that they accepted the status quo for a while. The fact that many choices in everyday life are made by individuals working for organisations or groups may also increase the compulsion to stick with the status quo. [44]

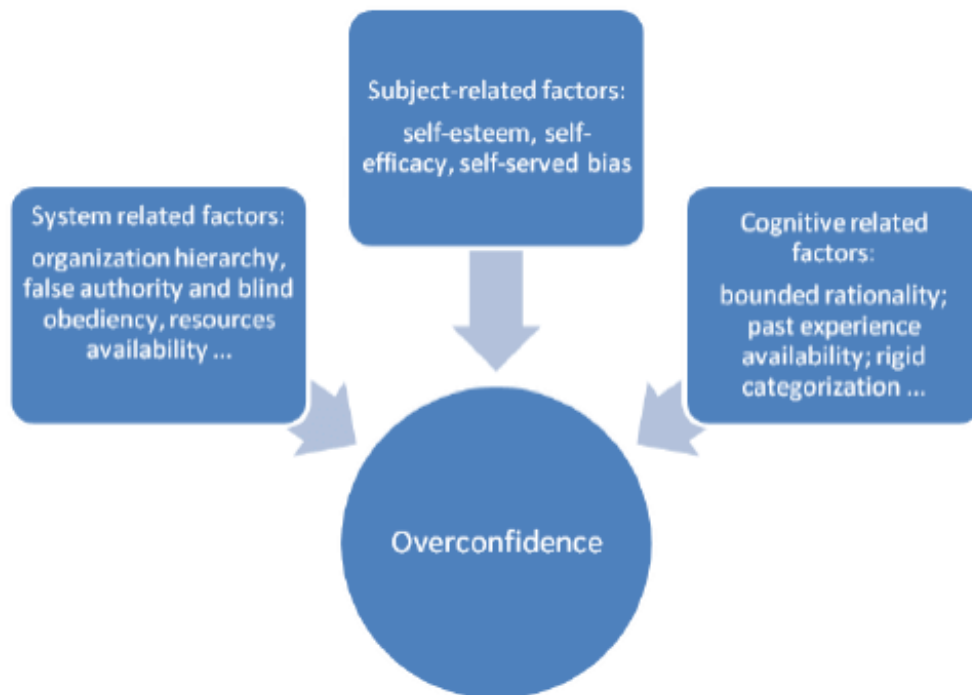


Figure 2.7: Sources of Overconfidence Bias [45]

### 2.3.8 Overconfidence Bias

Subjective confidence is largely unaffected by the strength or amount of the evidence. The quality of the story people can create about what they see, even if they don't see much, largely determines how confident they are in their ideas. We frequently fail to consider the possibility that the evidence we see is all there is and that other information that should be crucial to our judgment may be absent. Furthermore, the associative system is biased towards suppressing unpredictability and selecting a stable cycle of being activated. Although optimism is highly valued in society and business, truth-tellers are treated less favorably than dangerously misleading information providers. One of the key points learned from the economic recession that led to the recession of 2008 is that, occasionally, organisational and specialist rivalry can create potent dynamics that encourage a generalised lack of interest in uncertainty and risk. It seems that overconfidence is also common in healthcare. After-death findings were compared with the prognoses made by the patients' physicians during the time they were still alive in a study of hospitalised patients who passed away. Doctors expressed optimism as well. "Clinicians who were 'completely certain' of the prognosis pre-death were incorrect," was the outcome of this. 4 in 10 occurrences. [42]

### 2.3.9 Loss aversion Bias

Loss aversion is an essential psychological notion that is gaining prominence in economic research. Originally introduced by Kahneman and Tversky (1979) within their prospect theory, it evolved into a term for choice in a condition of complete certainty in 1991. Loss aversion is attractive because it can explain a lot of events that standard choice theory is unable to explain. One well-known example is the previously mentioned status quo bias. In behavioural finance, this bias has also been applied frequently in recent years. Loss aversion is defined as follows by Kahneman and Tversky (1979, p. 279): "An individual is loss averse if she or he dislikes symmetric 50-50 bets and, moreover, the aversiveness to such bets increases with the absolute size of the stakes." Without a doubt, this is a cognitive construct that can only be explained in relation to choices. The idea is therefore unconcerned with specific models. This idea of loss aversion is equivalent to a utility function that is more sharp for failures than for accomplishments, as Kahneman and Tversky (1979) showed in the previously mentioned theory setting. The utility function seems to be the only factor that reflects the impact of loss aversion because probability evaluation was not taken into account during the computation. Therefore, it should come as no surprise that utility has been the carrier of this bias in almost all research about it. For example, the authors of the theory also believed that utility was higher for failures than for accomplishments. In accordance with a numerical utility measure, Wakker and Tversky (1993) offer a choice criterion that is not dependent on probability evaluation. [46]

### 2.3.10 Decoy effect

One particular kind of psychological phenomena that influences decision-making is the decoy effect. It deals with the way surrounding conditions influence judgement. There is a wealth of research indicating that performance evaluations are likely to be influenced by surroundings. For example, the decision-making unit's (DMU) previous performance and the outcomes of other DMUs under analysis could influence the evaluator's decisions. The decoy effect proposes that the inclusion of a dominated choice—the decoy—may influence the choice made among the other alternatives. [47]

In particular, there may be a greater chance that people may choose the target alternative, the non-dominated choice closest to the decoy. Research on consumer behavior has frequently shown the presence of this impact, demonstrating that consumers tend to favor the target alternative. There are three primary categories of this effect: compromise effect, asymmetric dominance, and attraction effect. [47]

#### Attraction effect

The target choice (X) becomes more appealing when a decoy choice (D) is introduced to the set of two options (X and Y) in the attraction effect. Option X is superior to Option Y in the first characteristic but Y is superior in the second. Option D is just slightly superior to Option X in one characteristic, but Option X is superior to Option D in the second characteristic. [48]




product (robot)	X 	Y 	D 
price [0..10.000€]	5.000	2.000	4.900
reliability [0..10]	7	3	5

Figure 2.8: Decoy item (D) slightly predominates target item (X) in the domain of price, but is predominated in the domain of reliability. [6]

### Asymmetric dominance effect

This effect is the result of adding an inferior option to a decision set, which results in a systematic breakdown of rationality. To put it more precisely, it's the phenomenon that happens if you introduce an inferior alternative to the group of options that could make a particular alternative more likely to be selected. Take into account, for instance, a binary choice set with two possibilities, X and Y, each of which is distinguished by two characteristics. Assume that X is superior to Y in the first characteristic while Y is superior in the second. Typically, both X and Y are chosen in an experimental investigation. Let us now introduce a third option, D, which is dominated by either of the two options. The rationality principle states that the *decoy* alternative, which has just been offered, does not influence decisions. Due to another alternative in the decision set dominating it, it should essentially be disregarded. However, data suggests that the dominant alternative X's market share is significantly increasing, hence the name *target* [49].




product (robot)	X 	Y 	D 
price [0..10.000€]	3.000	1.000	3.500
reliability [0..10]	9	5	8

Figure 2.9: In terms of both features, Target option (X) dominates Decoy option (D). [6]

### Compromise effect

The phenomenon wherein individuals favor choices with non-extreme features over those with extreme attributes is relevant to the compromise effect. When faced with three options, such as Option X, Option Y, and Option D, take into account, for instance, a binary choice set with two possibilities, Y and D, each of which is distinguished by two characteristics. Assume that Option Y is superior in one characteristic and D is superior in the second. Suppose we insert a third option, X, which is dominated by one option in one characteristic but this option predominates in the second; in the second characteristic, it is dominated by another option but this option predominates in the first. The compromise effect predicts that the users will select Option X because it has important characteristics that are not extreme. [50]




product (robot)	X 	Y 	D 
price [0..10.000€]	3.000	1.500	5.000
reliability [0..10]	9	4.5	10

Figure 2.10: Target item (X) has non-extreme characteristics when compared to items Y and D. [6]

### 2.3.11 Position effect

One of the earliest topics in experimental psychology to be studied is position effects on human memory. The fundamental memory phenomenon known as serial location effects was originally studied in 1878 [51]. Short-term memory tests were where the effect was first discovered. It describes a process by which a collection of components—such as gibberish words, numbers, or names of everyday items that people had to learn beforehand—are recalled. In this case, there are two distinct patterns in the recall rate of elements from a collection: (1) elements at the very beginning of the collection are easier to remember compared to those in the centre, and (2) elements at the end of the collection are easier to remember compared to those in the centre. [52]

If an element is in an area where the user is not paying attention to it, even if it is necessary, it might not draw much interaction. Owing to the position effect, training relevance prediction models based on observed user-item interaction may be substantially skewed, with an item arbitrarily put higher on the ranking list receiving an unfair advantage, a disparity that may grow with each model update iteration. This bias not only impairs item relevance estimate, but when combined with position bias, it has the potential to silo users into fake relevant items, which has major consequences for platforms. [53]

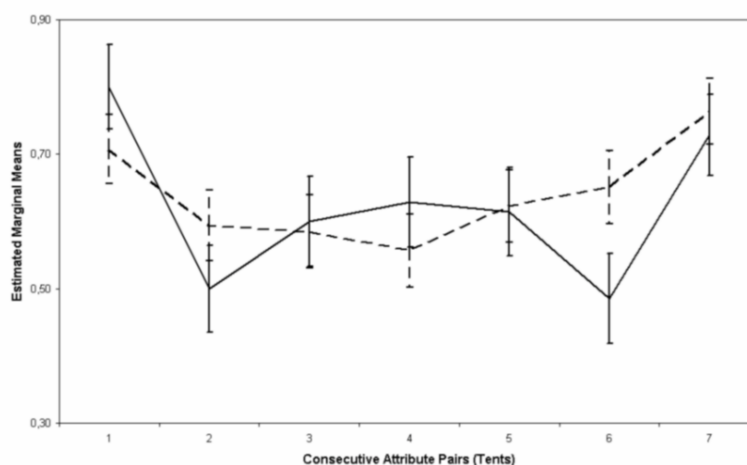


Figure 2.11: Position effect[53]

### 2.3.12 Explanations

Recommender systems provide consumers with additional suggested things. However, they are frequently seen as black boxes because no explanatory information is supplied about them. As a result, these suggestions might be accompanied by explanations of why a given item is suggested. Explaining the suggestions typically makes it easier for users to make decisions, raising conversion rates and enhancing satisfaction and trust in the system. An explanation is a description that validates recommendations and helps consumers determine whether or not the recommended item is relevant to their requirements. Giving explanations with suggestions would help consumers better comprehend the recommender system and provide a “feeling of forgiveness” if they did not like the new recommended goods. [54]

When developing an explanation services to serve a recommender system, it is important to consider the goal(s) of the explanation segment and what needs to be accomplished through integrating it into the programme. For instance, in an online store, a vendor might want to build trust with clients or persuade them to purchase particular products in order to foster loyalty. For instance, early healthcare expert systems often provided explanations concerning the underlying deduction rules of the system, enabling users to understand or evaluate the credibility of the medical opinion or guidance provided. It was soon discovered, though, that adding explanations wasn’t just for the purpose of understanding the system’s decision. Additional possible uses for expert systems include debugging, teaching, acceptance, and persuasion, according to Buchanan and Shortliffe [55]. Later, in [56] and [57], additional perspectives were added to this list, creating a more comprehensive list that is displayed in 2.12. [58]

These goals might be complementary (for example, effectiveness may improve trust) or incompatible (persuasiveness may diminish effectiveness). The relationships between goals are not always evident. For instance, relying on users’ confidence in the underlying system operation they are exposed to, transparency can boost or undermine trust. It is necessary to establish the main clarifying objectives before creating and assessing (optimal) explanations. Because optimizing one criterion may harm another, it is critical to analyze how the criteria interact with one another. [59]



Aim	Definition
Transparency	Explain how the system works
Scrutability	Allow users to tell the system it is wrong
Trust	Increase users' confidence in the system
Effectiveness	Help users make good decisions
Persuasiveness	Convince users to try or buy
Efficiency	Help users make decisions faster
Satisfaction	Increase the ease of use or enjoyment
Education	Allow users to learn something from the system
Debugging	Help users identify defects in the system

Figure 2.12: Aims of explanations [58]

Evaluations of explanation tools are presented, and possible modifications of existing criteria for determining the effectiveness of an explanation in a recommender system are also discussed. Some characteristics of explanations may help achieve a variety of objectives. For instance, one can rate an explanation's understandability, which can influence things like transparency, user trust, and satisfaction.

### Transparency

Its assessment frequently goes hand in hand with scrutability. However, it is feasible to inquire whether consumers are aware of how customization functions, such as whether they think suggestions are made based on similarities to other things or people, etc. Users might also be expected to help the system "learn" to like certain categories of objects, like the rock genre in a music recommendation system. Therefore, two important quantitative metrics would be the assignment's accuracy and its duration.

### Scrutability

Users could understand that the system's adaptation was based on the personal characteristics that were stored in their profiles, that these profiles contained information that the users voluntarily provided about themselves as well as information that the system deduced from its observations of them and that they could modify their profiles to manage the personalization.

### Trust

Surveys may be used to assess trust directly, while greater user loyalty and sales or system usage and login frequency can indirectly measure trust.

### Persuasiveness

The variation in the likelihood of picking a particular item can be used to quantify persuasion. It is feasible to determine if a user evaluates an item

differently after obtaining an explanation, in other words, if their judgment of the object has changed. Another option would involve comparing the accurate product testing and purchasing behavior in a system lacking an explanation capability with that in a system possessing this feature.

### **Effectiveness**

One approach to evaluating their effectiveness is assessing how well explanations are received before and after intake of the suggested item. A different approach would be to test the same system in both directions to see if individuals who are given explanations are generally happier with the products they selected.

### **Efficiency**

Efficiency can be determined by counting how long it took a user to find the item they were looking for in the web page or, in a more indirect way, by counting how many corrective actions and explanations they looked through.

### **Satisfaction**

Users can be explicitly asked if they prefer the system with or without explanations and whether it is enjoyable. User loyalty may be used to monitor satisfaction indirectly. [56]

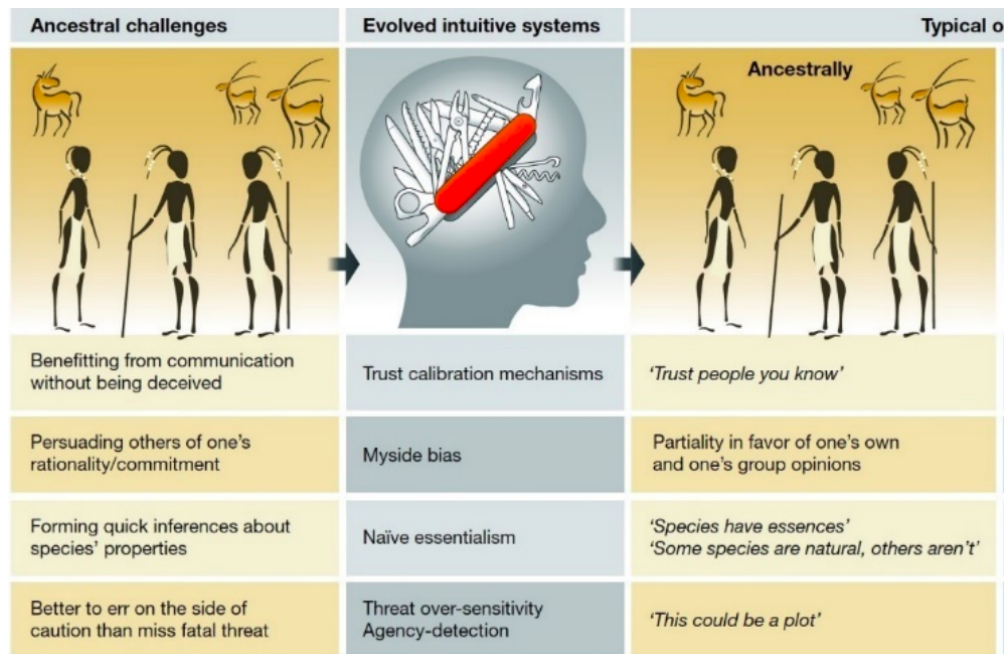


Figure 2.13: The Evolution of Bias [60]

2.13 demonstrates that bias, which appears to be irrational processing by the human brain, may be the result of an evolution of cognitive tradeoffs that proved beneficial to human survival. [60]

2.14 presents a list of twenty different cognitive biases with short descriptions below. Some of these biases are presented in this section in more detail.

## 2 Background and Related Work

**20 COGNITIVE BIASES THAT SCREW UP YOUR DECISIONS**

<p><b>1. Anchoring bias.</b></p> <p>People are <b>over-reliant</b> on the first piece of information they hear. In a salary negotiation, whoever makes the first offer establishes a range of reasonable possibilities in each person's mind.</p> 	<p><b>2. Availability heuristic.</b></p> <p>People <b>overestimate the importance</b> of information that is available to them. A person might argue that smoking is not unhealthy because they know someone who lived to 100 and smoked three packs a day.</p> 	<p><b>3. Bandwagon effect.</b></p> <p>The probability of one person adopting a belief increases based on the number of people who hold that belief. This is a powerful form of <b>groupthink</b> and is reason why meetings are often unproductive.</p> 	<p><b>4. Blind-spot bias.</b></p> <p><b>Failing to recognize</b> your own cognitive biases is a bias in itself. People notice cognitive and motivational biases much more in others than in themselves.</p> 
<p><b>5. Choice-supportive bias.</b></p> <p>When you choose something, you tend to feel positive about it, even if that <b>choice has flaws</b>. Like how you think your dog is awesome – even if it bites people every once in a while.</p> 	<p><b>6. Clustering illusion.</b></p> <p>This is the tendency to <b>see patterns in random events</b>. It is key to various gambling fallacies, like the idea that red is more or less likely to turn up on a roulette table after a string of reds.</p> 	<p><b>7. Confirmation bias.</b></p> <p>We tend to listen only to information that confirms our <b>preconceptions</b> – one of the many reasons it's so hard to have an intelligent conversation about climate change.</p> 	<p><b>8. Conservatism bias.</b></p> <p>Where people favor prior evidence over new evidence or information that has emerged. People were <b>slow to accept</b> that the Earth was round because they maintained their earlier understanding that the planet was flat.</p> 
<p><b>9. Information bias.</b></p> <p>The tendency to <b>seek information when it does not affect action</b>. More information is not always better. With less information, people can often make more accurate predictions.</p> 	<p><b>10. Ostrich effect.</b></p> <p>The decision to <b>ignore dangerous or negative information</b> by "burying" one's head in the sand, like an ostrich. Research suggests that investors check the value of their holdings significantly less often during bad markets.</p> 	<p><b>11. Outcome bias.</b></p> <p>Judging a decision based on the <b>outcome</b> – rather than how exactly the decision was made in the moment. Just because you won a lot in Vegas doesn't mean gambling your money was a smart decision.</p> 	<p><b>12. Overconfidence.</b></p> <p>Some of us are <b>too confident about our abilities</b>, and this causes us to take greater risks in our daily lives. Experts are more prone to this bias than laypeople, since they are more convinced that they are right.</p> 
<p><b>13. Placebo effect.</b></p> <p>When <b>simply believing</b> that something will have a certain effect on you causes it to have that effect. In medicine, people given fake pills often experience the same physiological effects as people given the real thing.</p> 	<p><b>14. Pro-innovation bias.</b></p> <p>When a proponent of an innovation tends to <b>overvalue its usefulness</b> and undervalue its limitations. Sound familiar, Silicon Valley?</p> 	<p><b>15. Recency.</b></p> <p>The tendency to weigh the <b>latest information</b> more heavily than older data. Investors often think the market will always look the way it looks today and make unwise decisions.</p> 	<p><b>16. Salience.</b></p> <p>Our tendency to focus on the <b>most easily recognizable features</b> of a person or concept. When you think about dying, you might worry about being mauled by a lion, as opposed to what is statistically more likely, like dying in a car accident.</p> 
<p><b>17. Selective perception.</b></p> <p>Allowing our expectations to <b>influence how we perceive</b> the world. An experiment involving a football game between students from two universities showed that one team saw the opposing team commit more infractions.</p> 	<p><b>18. Stereotyping.</b></p> <p>Expecting a group or person to have certain qualities without having real information about the person. It allows us to quickly identify strangers as friends or enemies, but people tend to <b>overuse and abuse</b> it.</p> 	<p><b>19. Survivorship bias.</b></p> <p>An error that comes from focusing only on surviving examples, causing us to <b>misjudge a situation</b>. For instance, we might think that being an entrepreneur is easy because we haven't heard of all those who failed.</p> 	<p><b>20. Zero-risk bias.</b></p> <p>Sociologists have found that <b>we love certainty</b> – even if it's counterproductive. Eliminating risk entirely means there is no chance of harm being caused.</p> 

**SOURCES:** Brain Biases; Ethics Unwrapped; Explorable; Harvard Magazine; HowStuffWorks; LearnVest; Outcome bias in decision evaluation, Journal of Personality and Social Psychology; Psychology Today; The Bias Blind Spot: Perceptions of Bias in Self Versus Others, Personality and Social Psychology Bulletin; The Cognitive Effects of Mass Communication, Theory and Research in Mass Communications; The less-is-more effect: Predictions and tests, Judgment and Decision Making; The New York Times; The Wall Street Journal; Wikipedia; You Are Not So Smart; ZhurnalWiki

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Figure 2.14: Cognitive biases [60]

## 2.4 Food Recommendations

The World Health Organization (WHO) notes that nutrition significantly impacts our overall wellness and health and can help prevent many chronic diseases, including diabetes, obesity, cancer, and cardiovascular diseases. Making dietary decisions is a difficult, multi-step process that depends on several factors unique to each person, including education, culinary preferences, emotions, hunger level, health status, the necessity for a specific diet, ethnic background, and personal budget. In most countries, it has become a pleasurable activity and an essential part of social life. Environmental elements like weather conditions, the period of day, the surroundings, or marketing can also have an impact on food preferences. Food preferences can also be impacted by indirect variables beyond one's control. For instance, governmental regulations may impact food production costs, which may subsequently be passed on to consumers. The ensuing price fluctuations may affect purchases of food. People's decisions on what to eat are becoming increasingly influenced by search and recommendation systems: Internet recipe portals are a widely used source of culinary inspiration and frequently let users review and receive recipe ideas. It is well acknowledged that humans frequently make judgments based on heuristics rather than a logical comparison of the available possibilities because they have limited cognitive resources. Heuristics can be pretty effective. However, there are several ways in which eating decisions might be skewed. People frequently make bad choices when emotionally or stressfully aroused, for example, when hungry and surrounded by the sights and scents of calorie-dense food. People adjust their behavior to the social situation in which they find themselves: it is more common for overweight people to be friends with other overweight people, and eating in groups increases consumption. [61]

Online food services are rapidly creating food recommendation systems that provide consumers with recommendations based on their past dietary regimens. While inadequate nutrition can cause major illnesses, the majority of sophisticated food recommendation systems do not take physical wellness into account when making recommendations. This highlights how important it is that the advice be trusted when it comes to topics related to health. [62]

Food types have become so diverse and complicated that humans require professional assistance to make the best choices, especially since food has become a global parameter. The Food Recommendation System is an intelligent system that advises beneficiaries on the best options based on their needs. Furthermore, other types of dietaries in other foods affect human activities and lifestyle. Everyone must understand what nutrition they require. [63]

There are three distinct categories of modern food recommender systems; the first ones were developed in the 1980s. The first kind of recommender

resembles conventional methods in other recommender areas and optimises suggestions considering user tastes or feedback. In the food domain, the second strategy—which prioritises satisfying the user’s dietary requirements—may be more unique. By integrating user restrictions like food intolerance with preference information, a third approach often strikes a compromise between dietary requirements and user preferences. User-preference-based food recommender systems solely take into account foods that the consumer may like according to generated preference. Most methods combine content-based recommendation and collaborative filtering, with user feedback or retrieval of corresponding item serving as a vital element. [64]

The efficacy of hybrid, content-based, and collaborative filtering methods is compared by Freyne and Berkovsky [65]. The most successful strategy breaks down dish evaluations into ingredient evaluations using a content-based method. Users seem to favour dishes with similar ingredients (pasta, for example) to ones they have liked in the past.

Food recommender systems have undergone significant changes due to the recent rise of customised applications meant to provide assessments and recommendations while making purchases, the growing popularity of smartphone devices, the creation of significant virtual and community-sourced databases striving to catalogue databases of food products from across the globe, and more. Although recent studies have begun to look into how these applications affect users’ behavioural patterns and the core ethical dilemmas they raise, their main goal is to strengthen the consumer’s “Right to Know” while also articulating the modern trend of “information activism.” Unlike conventional consumerist magazines, these applications are nearly always available, which lessens the abstract nature of the connection between buyers and the market. The fact that millions of users are using these applications means that their recommendations impact both producers and consumers. These applications usually strike a balance between technological unpredictability (e.g., details about products in records may be false or useless), customer issues (e.g., real-time operation delivering information, evaluations, and suggestions on an extensive range of products; expenses and product accessibility), and scientific reasoning (e.g., the evaluations and ratings given to food items don’t always align with scientific accuracy). [65]

Like other recommender systems, food recommender systems are also subject to the influence of various decision biases. Decoy effect, Position effect, and Explanations are just one of the many biases used to nudge the customer’s decision when choosing a recipe or ordering food. [65]

### 2.4.1 Architecture of Food Recommender Systems

This architecture, which consists of four layers handling information flow from the user data tier to the last-stage suggestion creation, is shown in 2.15. The four layers are as follows:

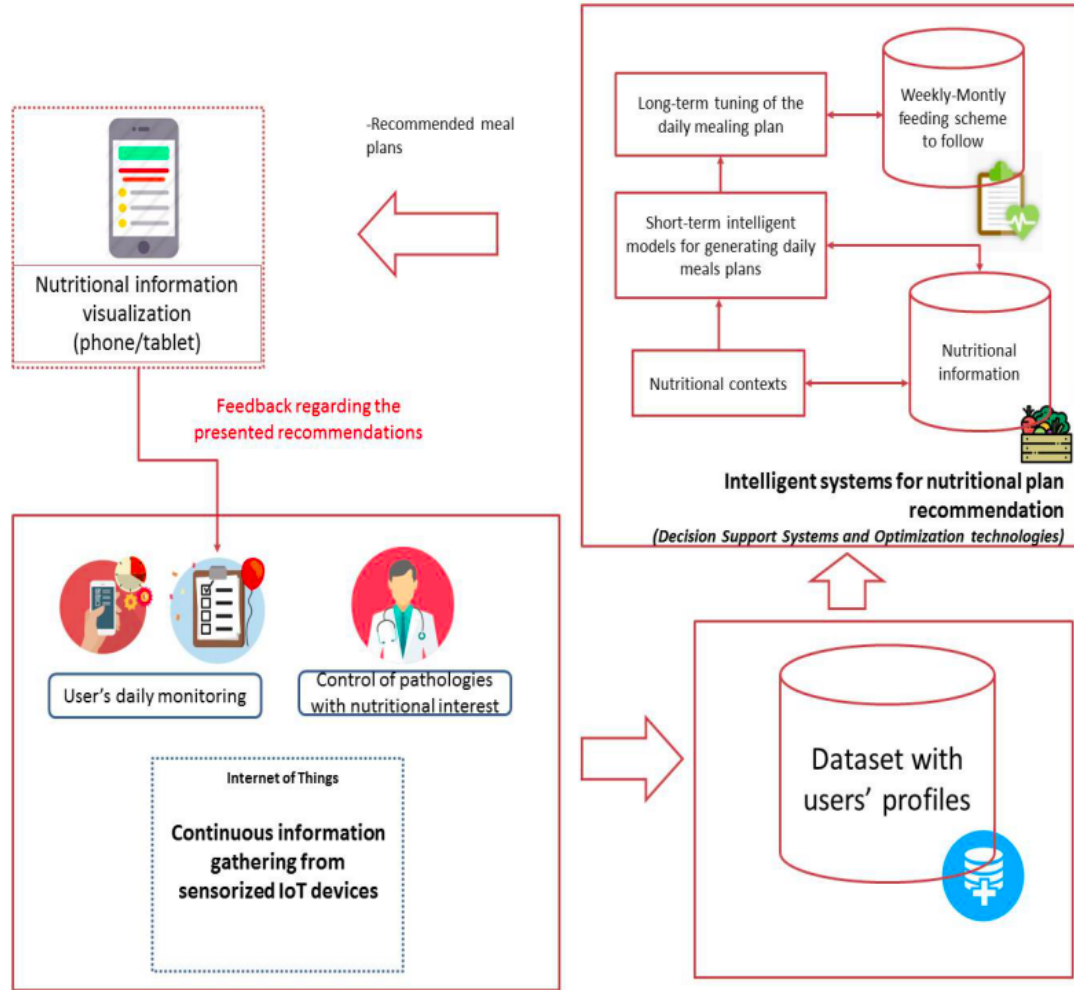


Figure 2.15: Architecture of Food Recommender Systems [66]

All essential dietary data associated with the consumer must be gathered by the information collection layer. The user-provided data contains daily dietary habits and scientific expertise, which includes nutritional tables and dietary restrictions, in addition to physiological details like the user's measurements, pulse, expended calories, and daily exercise intensity. Consequently, this tier is highly dependent on sensorized Internet of Things (IoT) gadgets for ongoing data collection to build the user account accurately. [66]

The data that will be used to describe people and serve as information feeding

into the dietary suggestions method is the main focus of the customer profile information. Simply speaking, the information gathered by the information gathering tier is going to be included in this information set, which will allow suggestions to be generated based on criteria that are nutritionally aware (backed by physiological measurements) and selection-conscious (backed by previous daily dietary consumption). [66]

The information about the user's profile is received as input by the intelligent systems section, which then outputs the suggested diet regimen. The knowledge of dietitian is also actively utilised in this section, as intended by the knowledge gathering section. Three main parts make up the intelligent systems section: First, the dietary circumstances are determined. This involves first eliminating certain items that are not suitable for the recommendation that are made for the consumer utilizing the tool. Secondly, short-term intelligent models are used to generate daily eating regimens. These models improve consumer choices over recommended dishes while checking the required nutrients. Lastly, long-term intelligent models are used to refine the daily regimen by considering nutrition goals that need to be followed on a weekly and monthly basis. [66]

An interface designed to provide suggested food regimens along with extra visual representation of nutritional data. Furthermore, this interface aims to gather user input based on the recommendations that are provided. The information management segment receives the aforementioned data and uses it continuously for the characterization of the customer. [66]



### 2.4.2 Examples of Food Recommender Systems

#### Market2Dish

[67] presents Market2Dish, a customised health-conscious meal recommendation system that links the products available at the grocery store to the wholesome meals consumed at home.

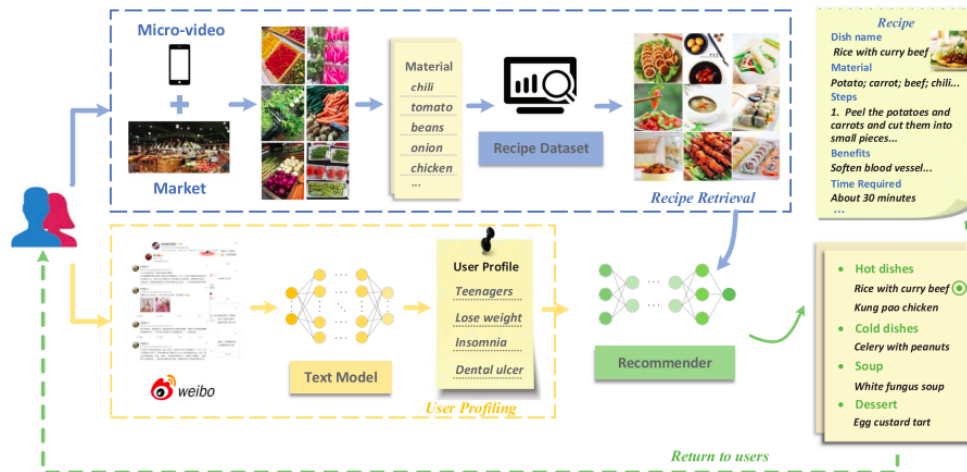


Figure 2.16: Market2Dish [67]

**Recipe Retrieval.** The aim of this section is to retrieve potential recipes from substantial recipe collections and then collect ingredients that are easily accessible to the user. Consumers can contribute elements for the suggested design in a variety of methods, such as by choosing among the candidates, speaking, or entering micro-videos. [67]

**User Health Profiling.** Online social media platforms, with their billions of members, have provided an immense amount of customer information for dietary tracking and forecast. Regarding user profiling, a number of innovative methods for identifying trends in behavioural patterns inside social media platforms have been put forth. Significant content created by consumers distributed over social media platforms is used to develop a guided neural model for consumer wellness profiling. Medical professionals work together to assess a variety of factors, including demographic factors and prevalent illnesses. They then support the system in putting forth a number of health-related labels that describe the common traits and medical conditions of a range of people, including teenagers, athletes, and people with diabetes. Remarkably, all users have the minimum of one health-related label (age or work related), and most have many. This will convert creating a comprehensive health profile of the user

into a multi-label classification issue: According to user-generated content on social media platforms, the proposed model would assign the user to single or multiple categories. [67]

**Recipe Recommendation.** The health-conscious user-recipe interactions can train the recommender. In reality, there are close relationships not just between people with comparable health-related labels, but also between dishes with similar nutritional contents. It makes sense that people struggling with comparable health conditions would follow similar eating habits; that is, recipes made with equivalent goods will benefit those in a particular user category. Hierarchical memory system with category awareness discovers resemblance within categories and distinction between categories in order to explicitly use these associations to enhance dish suggestion effectiveness. According to their health-related labels, all users are divided into  $X$  groups, and the dishes are divided into  $X_c$  groups according to how they meet specific health requirements, like a calorie-restricted diet and dietary supplements. Particularly, a single user and food may fall under more than one category because of numerous health-related labels or nutritional values. [67]

**PlateClick**

PlateClick is a novel method of effectively eliciting meal choices through the usage of a straightforward, interactive visual questionnaire interface. PlateClick provides a visually appealing interface and does a comprehensive examination of food photos to get over the limitations mentioned previously. This marks the primary algorithm and system that uses in-the-moment communication to discover customers' dietary preferences without requiring prior dietary record. This approach was designed to be a quick, easy-to-use, web-based tool that can be fulfilled in a single minute. PlateClick's system architecture is shown in 2.17. As mentioned below, it consists of multiple elements in both non-digital and digital phases. [68]

**Information Retrieval** After extracting 12 thousand primary food recipes along with their photos and information, and removing picture anomalies, 10,028 culinary products from a variety of culinary traditions are included within the ultimate set of data. [68]

**Embedding** To improve comprehension and manage an extensive amount of culinary products, the image proximity measure is observed. [68]

**Frontend** To get preferences for food, there are several phases in the procedure. The advantages of side-by-side assessment and visual choice in interface layout are explored, both of these have the possibility to provide better outcomes. Customers are asked to tap on each of the 10 photographs that they find appealing in the initial pair of versions. In every subsequent repetition, users are shown with two images of meals, and they are prompted to either press the item they like most or press yuck to indicate they have no desire for either. [68]

**Backend** The innovative algorithm at the core of the system looks at how comparable meals are to one another. [68]

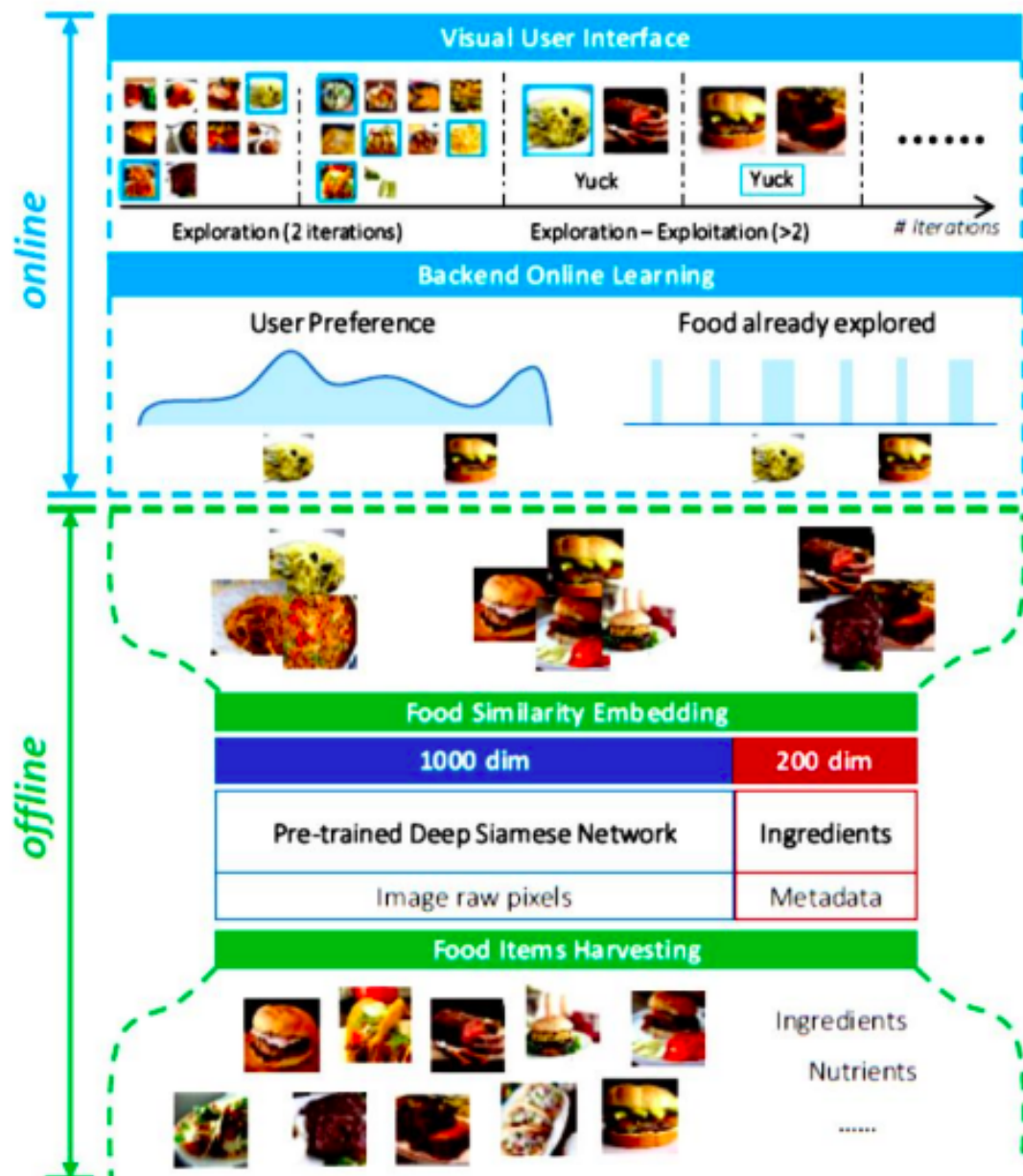


Figure 2.17: PlateClick [68]

### **Real-time Mobile Recipe Recommendation System**

System for recommending mobile cooking recipes that use object recognition for components like meats and veggies. On an Android-based smartphone, the suggested system performs object identification on food items in real-time and suggests cooking recipes based on the identified ingredients. A user may quickly get a recipe list by just pointing a mobile device's built-in camera at culinary components. [69]

Step 1: Aim a smartphone camera at food components in a kitchen or at a grocery store. The camera gadget in the background is continually providing frame pictures to the system.

Step 2: Continuously identify food elements in the obtained frame pictures. On the mobile device's screen's upper right corner are displayed the top six options.

Step 3: To retrieve a menu list, use the title of the identified food item as your query to visit online cooking recipe databases. If a user wishes to search for recipes using ingredients other than the top pick, they can select the six most relevant items by pressing the screen.

Step 4: Display the obtained menu set on the left portion of the display.

Step 5: From the set of options, select a menu. A user can examine choices that are not initially presented on the display by continuing to scroll.

Step 6: Display the corresponding cooking instructions for the chosen dish in a new window together with a list of the necessary ingredients and spices. It will effectively display the cooking directions from the primary recipe website.

The suggested system is often used by a user in accordance with steps one through six above. The system screen is seen in 2.19. [69]

## 2 Background and Related Work



Figure 2.18: Processing flow [69]

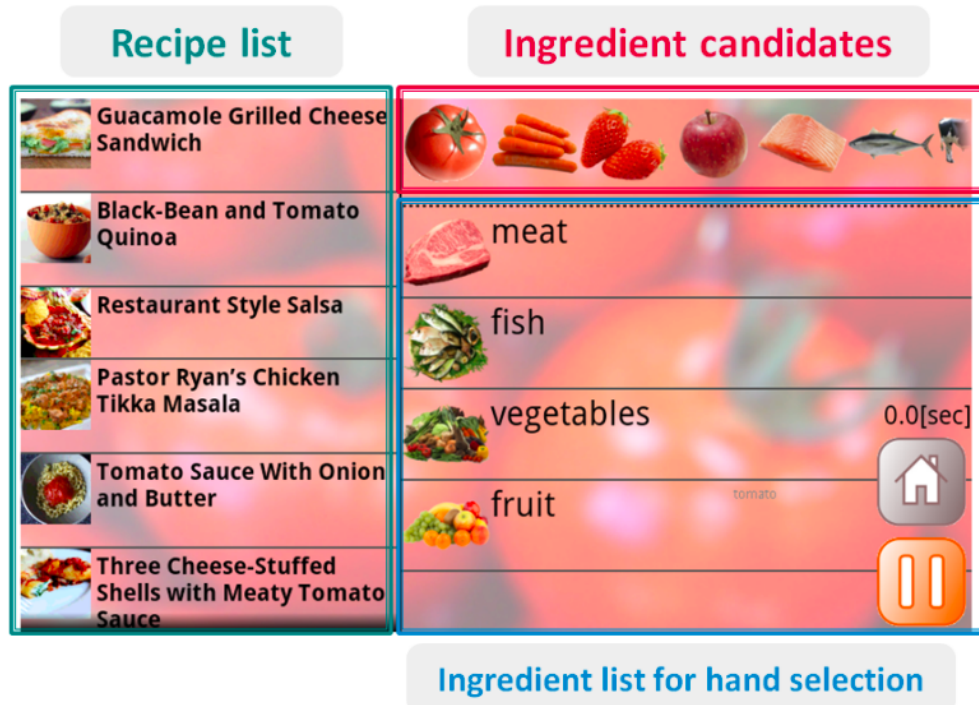


Figure 2.19: The system screen [69]

## 2.5 Related work

There is a significant amount of research on the Decoy Effect, Position Effect, and Explanations. In this section, we will present part of that research to discover what facts are missing and show the need for a user study which is presented in the next chapter.

### 2.5.1 Decoy Effect

The asymmetric dominance strategy was applied in [70], where authors tried to promote a healthy snack in the workplace in the USA. They placed the withered apple as an inferior option to increase the attractiveness of the shiny Fuji apple when considered together with a cookie. The implemented decoy-based nudging mechanisms had no significant effect on user snack choices.

[71] examined the compromise effect on consumers' decisions about pork products when presented in a predictable order. Additionally, the authors looked at the effects of various types of decoy information and whether the respondents were given the information before or after deciding without any decoy information. Consumer choices about pork purchasing exhibited a strong compromise effect. In this research, decoy material presented as high-priced and low-priced information exhibits the compromise effect. However, the compromise effect disappeared when consumers made a pick with no decoy data and then made a different choice after learning about the decoy. Instead, their selections were equally spread among all the products in the option set. This illustrates how adjustments in how decoy information was presented affected customer behavior.

The decoy effect was also proven in [72] on real e-commerce websites. The selection rate for the decoy items was lower than that of the competitor and target item when they were substituted with a regular item. The target item's pick rate was reduced more than the competitor's, indicating a decrease in the cognitive bias that previously increased the probability of the target items being selected. On the other hand, the decoy effect on meal choice did not have a main influence in [3].

### 2.5.2 Position Effect

In [73], a real-life study is conducted at a Swedish university canteen where the menu is randomised to place vegetarian choice at the menu's forefront (treatment) or the vegetarian choice at the menu's end and the meat choice at the menu's forefront (control). The meat items sales ratio drops dramatically when the vegetarian choice is listed first on the menu. It follows that stimu-

lating people to choose environment-friendly food options is effective when it comes to diet-related circumstances. The considerably unfavourable effect on the percentage of meat options favours the ratio of fish and vegetarian options offered, even when the overall customer count does not decrease when the vegetarian option is placed at the menu's forefront.

Several other areas related to recommendations also looked into these effects. For example, the position effect was also proven in News Recommendations in [74]. This paper demonstrates a sharp decline in clicks per position. Items in the first position receive more than 4% of all clicks. Lower classes receive fewer clicks. Almost 90% have fewer than three clicks.

Regarding the specific position effect, the primacy effect was also demonstrated in [75]. Customers showed a higher tendency to select healthier dishes on a recipe website when they were shown a list of search results ordered by health rather than popularity. The authors have highlighted how various picture features relate to visual appeal and how user preferences are impacted by an image's visual appeal, citing the fact that when paired with an attractive image, healthier recipes were more inclined to be chosen. They have provided assistance with experiments that demonstrate how individuals are inclined to favour visually pleasing food photographs and how certain picture attributes may indicate an image's popularity or beauty. It has also been demonstrated that the presentation order effect has large impact sizes. According to psychological studies, people tend to like items that appear first, which is consistent with this finding. The popularly known as "edge effect," in which options placed at both ends of a list tend to be chosen more often, has been seen in research analysing restaurant menus; however, no evidence of "end of list" tendencies has been identified. Rather, it seems that the dishes are arranged online according to the "first come, first served" rule.

### 2.5.3 Explanations

In [76], Cora—a dialogue-driven recommendation platform—was explained. It suggests dishes based on users' dietary preferences and needs. Cora could communicate with its customers using text, controls, and selectable menus, and include them in purpose-driven conversations or relationship-building activities. This platform might additionally provide more suggestions and explain the compromises among options in order to support its position. After that, the writers polled customers to see how Cora's justifications and suggested matches affected their opinions of the software. The results imply that consumers' opinions of a recommender system are positively impacted by explanations. But drawing a comparison between a decoy and a nourishing food was both benefit and burden. Despite the fact that people found a comparison of this kind to



be far more instructive than a single healthy advice, people were less inclined to adopt the method when they could clearly differentiate the nutritious dish from the decoy. Additionally, the outcomes showed that Cora may influence its customers to follow suggestions that were considered more nutritious compared to what they would usually prepare.

In [77], the growth and effects of a concept for Active Learning critique-based mobile recommender systems in the fashion industry were examined. The created approach suggests creating explanations to increase system transparency while also using them as a tool to give users greater influence over making recommendations. Also, the idea describes user input as a combination of criticism and explicit declarations of current interests. A technique for producing explanations is created using a content-based recommendation methodology. The explanations are always interactive to allow the user to fix any potential system errors. A mobile Android app was created utilizing the suggested idea and the explanation-generating algorithm to assess the concept's applicability. Explanations and especially interactive explanations significantly increased the user's satisfaction.

Authors in [78] have created a procedure that enables quantitative analysis of how explanations affect users' decisions while receiving item recommendations. A managed approach to bias introduction using a mix of favorable and unfavorable elements, manual item aspect extraction for explanations, preference elicitation, which enables the creation of customised recommendations, and the delivery of explanations in dual text styles are all significant elements of this design. This user survey demonstrated that explanations could significantly impact people's choice of items.

#### **2.5.4 The combination of Explanations and Position Effect**

The objective of [79] was to examine a nudge to encourage making good food choices in a challenging real-world environment. The authors concentrated on consumer acknowledgment of the nudge and the impact from revealing the nudge to its targets in addition to its efficacy. From this investigation, three key findings may be derived. First, moving goods around has a significant influence on what people will eat. In keeping with the expectations, after just one week of being placed close to the cash register desk, sales of healthy items virtually quadrupled (287 versus 161). Despite its ease of use and low cost, this intervention has the potential to be an effective way to encourage consumers to choose better food options. A second discovery shows that putting up a banner that says, "We support you in selecting a healthy option," adjacent to the cashier counter was not able to decrease the efficacy of the nudge or boost purchases of healthy products. Even while it can be claimed that such a sign

is no longer necessary, it nonetheless sends a crucial message: being open and honest about pressuring customers to purchase healthy food items eases the majority of ethical or moral objections to the action taken. The study's final finding is that most individuals place a high value on healthy eating. Thus it is not unexpected that most consumers responded favorably to the intervention. 85% of the clients said they were open to assistance in making healthier dietary choices. This would suggest that a company or authorities could only profit concerning reputation from activities meant to help its clients or constituents achieve their (health) goals, in addition to increasing revenues.

### 2.6 Summary

As seen from previously described articles, there have been many different pieces of research on decision biases in Recommender Systems, including Food Recommender Systems. Decoy effect, Position effect, and Explanations in Recommender Systems are among the literature's most popular and most analyzed biases. However, in this paper's context, few articles compare the effects of decision biases and their combinations. Therefore, there is a need for a user study to reach the results of the Decoy Effect, Position Effect, and Explanations alone and in combinations of two or three on a user in a Food Recommender System.

## 3 User Study

In this user study, we will empirically test the influence of the Decoy effect, Position effect, and Explanations, both individually and in combinations, in Food Recommender Systems. Their influence has been proven both in Food Recommender Systems and in others, so it is of great interest to combine these effects in order to test their success. This kind of user study will enable us to test individual success and compare all effects as well as their combinations to find the best suitable solution for this type of Recommender System. Our research question is "Are the Decoy effect, Position effect and Explanations and their combinations successful in persuasion in Food Recommender Systems, and are these combinations more successful than the effects individually?".

### 3.1 Hypotheses

Three suggested decision biases might work well to persuade people to choose a healthier food choice. Users may be persuaded to modify their preferences for recipes by placing the healthy recipe first, including a decoy item, or displaying the recipe attributes to them. Seven different hypotheses are tested in this paper.

- H1: Decoy effects will increase the choice of the target item (healthy recipe),
- H2: Position effects will increase the choice of the target item (healthy recipe),
- H3: Explanations will increase the choice of the target item (healthy recipe),
- H4: Decoy and position effect in combination will increase the choice of the target item (healthy recipe) more than they did individually,
- H5: Decoy effect and explanations in combination will increase the choice of the target item (healthy recipe) more than they did individually,
- H6: Explanations and position effect in combination will increase the choice of the target item (healthy recipe) more than they did individually,
- H7: Decoy effect, position effect, and explanations in combination will increase the choice of the target item (healthy recipe) more than they did individually and more when only two of them were combined.

## 3.2 Implementation

For this study, a web application consisting of ten different interfaces was created. Every user was assigned to a certain interface randomly. The user had to fill in the personal data and then choose one recipe from each of the six groups of recipes. The amount of six groups is enough to make useful conclusions without tiring the participants. We tried to avoid burdening the participants because it could affect the quality of the answers.

Depending on the assigned interface, a user was supposed to be persuaded by the position effect, decoy effect, explanations, or a combination of two or three mentioned effects, to choose the target item (healthy recipe). One interface did not contain any of the above effects.

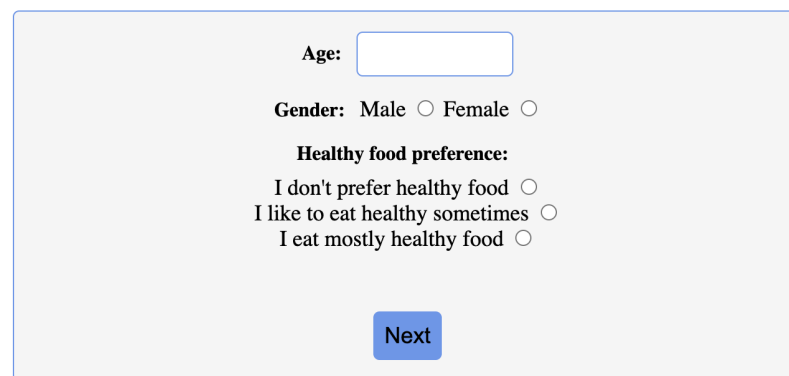
A screenshot of a web form titled 'Personal Data'. The form is enclosed in a light gray rounded rectangle with a thin blue border. It contains three sections: 'Age:' followed by a white text input field; 'Gender:' followed by 'Male' and 'Female' options, each with an unselected radio button; and 'Healthy food preference:' followed by three options: 'I don't prefer healthy food', 'I like to eat healthy sometimes', and 'I eat mostly healthy food', each with an unselected radio button. At the bottom center of the form is a blue rectangular button with the word 'Next' in white text.

Figure 3.1: Personal Data

As shown in Figure 3.1, every user had to fill in their age, gender, and healthy food preference to continue with the survey. In Figure 3.2, Figure 3.3, Figure 3.4, Figure 3.5, Figure 3.6, and Figure 3.7, all of the six groups of recipes in interface consisting decoy effect, position effect, and explanations are shown. The order of these six groups is randomized to avoid additional decision biases. In other interfaces, groups of recipes are identical as in this one, just with a different order in interfaces without position effect, without decoy item in interfaces without decoy effect, or recipe attributes above the recipes in interfaces without explanations.

### 3.2.1 Decoy effect

Among three different types of the decoy effect, we chose to impact users with the *attraction effect*. The decoy item always has a slightly shorter preparation time than the target item, but the target item has a better Nutri-Score than the decoy item. The decoy item always has a better Nutri-Score than the competitor item, but the competitor item always has a shorter preparation time than the decoy item. By adding this decoy item, we tested the success of the *attraction effect*. To avoid additional nudges, we have tested the decoy effect in three different scenarios, only differing in the position of the decoy item. In scenarios where the decoy effect is combined with other effects, the decoy item is always shown in the middle. As a result, the current study analyzes whether the presence of the decoy item, which is slightly better than the target item in one attribute (preparation time) but worse in another attribute (Nutri-Score), influences user selections for healthy dishes.

### 3.2.2 Position effect

We anticipate that a presentation order impact can also be employed to promote healthier recipes. Due to the *primacy effect*, ordering recipes based on healthiness may increase the selection of more nutritious options. By putting the healthy option first, we tested the success of the *primacy effect*. As a result, the current study analyzes whether ranking recipes based on their healthiness influences user selections for healthy dishes.

### 3.2.3 Explanations

To encourage users to choose healthier recipes, they are presented with two attributes. The first attribute is the Nutri-Score. One example of a directive, interpretive label is Nutri-Score, health indicator without nutritional specifics. It utilizes explanatory color labeling using the recognised signal light colours of green, yellow, and red together with data on nutrition. According to this, the Nutri-Score tag uses colouring and characters within the range of A through E to determine the nutritional value of products both within and across food groups. [80]

The second recipe attribute is the time needed to prepare the dish. As a result, the current study analyzes whether displaying Nutri-Score and the required effort of recipes influences user selections for healthy dishes.

Table 3.1: Nudges present in hypotheses

	H1	H2	H3	H4	H5	H6	H7
Decoy effects	x			x	x		x
Position effects		x		x		x	x
Explanations			x		x	x	x

### 3.3 Participants

All 202 participants are students of the Technical University of Graz, where 150 are males (74.26%), and 52 of them are females (25.74%).

The participants are between 18 and 32 years old.

Among the participants, 93 of them prefer to eat only healthy food (46.04%), 102 prefer to eat healthy sometimes (50.5%), and only 7 of them don't prefer eating healthy food (3.46%).

Of 52 females, 23 prefer to eat healthy food (44.23%), 28 prefer to eat healthy food sometimes (53.85%), and only one doesn't prefer to eat healthy food (1.92%).

Of 150 males, 70 prefer to eat healthy food (46.67%), 74 prefer to eat healthy food sometimes (49.33%), and only six don't prefer to eat healthy food (4%).

Choose your preferred recipe:

1/6

*Air Fryer French Toast Sticks*

NUTRI-SCORE: A, REQUIRED EFFORT: 4.5

☐

*Air Fryer French Toast*

NUTRI-SCORE: C, REQUIRED EFFORT: 4

☐

*Baked French Toast*

NUTRI-SCORE: E, REQUIRED EFFORT: 1.5

☐

OK

Figure 3.2: Every user has to choose one of the offered French toast options: healthy, decoy, or unhealthy item

Choose your preferred recipe:

2/6

*Clean Banana Oat Cookies*

NUTRI-SCORE: A, REQUIRED EFFORT: 4.5

☐

*Crisp Oatmeal Cookies*

NUTRI-SCORE: C, REQUIRED EFFORT: 4

☐

*Chocolate Mint Cookies*

NUTRI-SCORE: E, REQUIRED EFFORT: 1.5

☐

OK

Figure 3.3: Every user has to choose one of the offered cookies options: healthy, decoy, or unhealthy item

Choose your preferred recipe:

3/6

*Delicious Cinnamon Baked Apples*

NUTRI-SCORE: A, REQUIRED EFFORT: 4.5

☐

*Baked Apples*

NUTRI-SCORE: C, REQUIRED EFFORT: 4

☐

*Baked Apple Cider Donuts*

NUTRI-SCORE: E, REQUIRED EFFORT: 1.5

☐

OK

Figure 3.4: Every user has to choose one of the offered apple sweet options: healthy, decoy, or unhealthy item

### 3 User Study

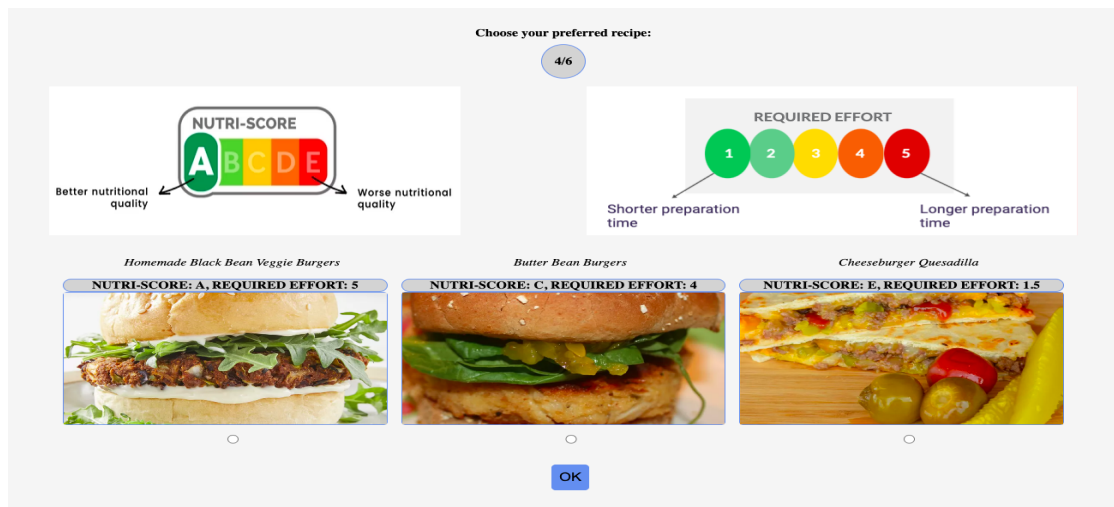


Figure 3.5: Every user has to choose one of the offered burger options: healthy, decoy, or unhealthy item

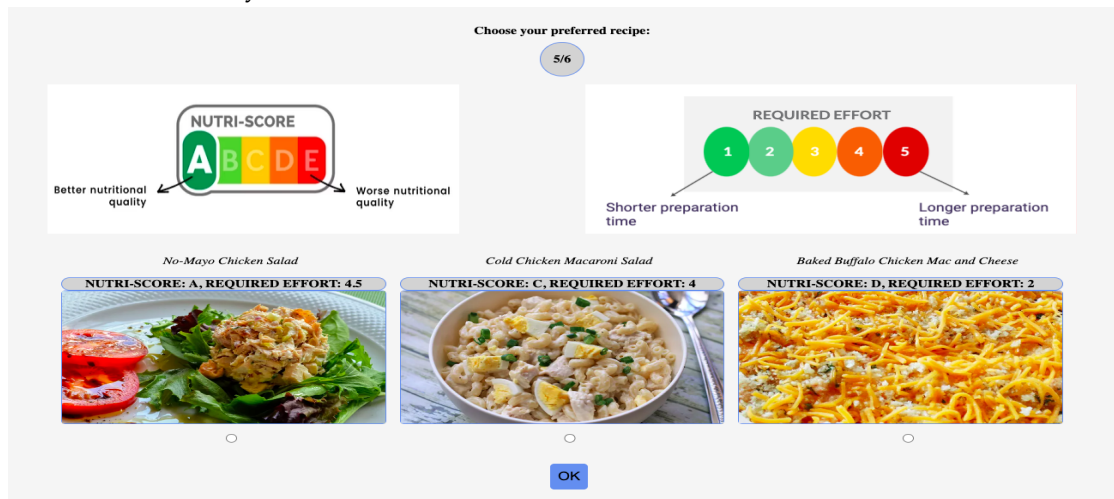


Figure 3.6: Every user has to choose one of the offered chicken options: healthy, decoy, or unhealthy item

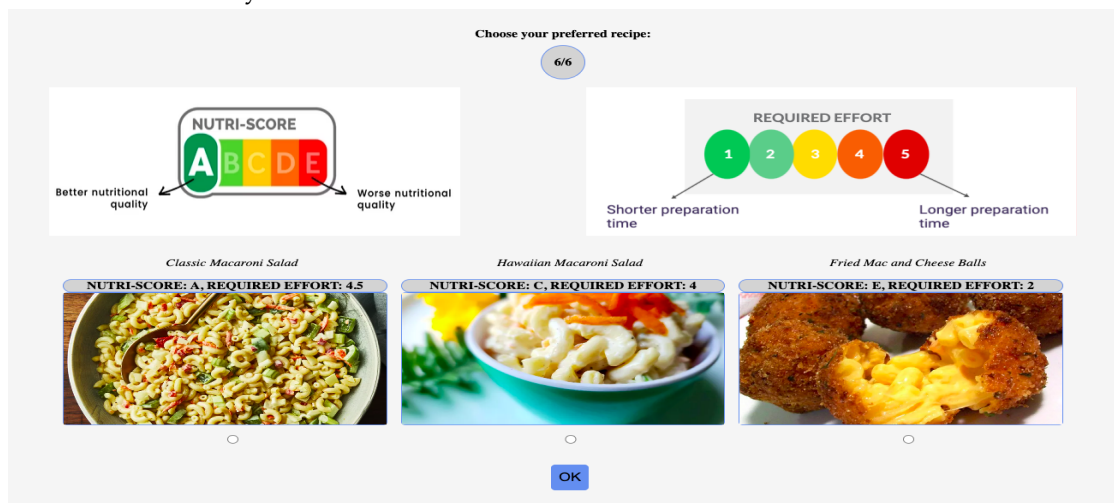


Figure 3.7: Every user has to choose one of the offered macaroni options: healthy, decoy, or unhealthy item



## 4 Discussion and Evaluation

Participants were assigned to interfaces with different effects randomly, where every user was assigned to only one interface (between-subjects (or between-groups) study design). Each user had to make six choices between either healthy and unhealthy items, or healthy, unhealthy, and decoy items. With 202 participants, that is 1212 choices. For a clearer evaluation, all recipes are presented separately. Additionally, effects are separated, so we can discuss the success of the hypotheses. For better visibility, the results are also presented in tables, where for every effect and every recipe, the number of participants who chose healthy, decoy or unhealthy items can be found in the dedicated cell.

The rate of healthy options is found by dividing the number of healthy choices in that interface (e.g. in the interface with no effect this number is 55) by the total number of choices in that interface (for the interface with no effects, this number is 120 because this interface was assigned to 20 users, and every user had to make 6 choices) and then multiplying the result by 100. Also, this rate is found for each recipe separately by dividing the number of healthy choices in that interface for this exact recipe (e.g. in the interface with no effect and for recipe 1 this number is 10) by the total number of participants in this interface (e.g. in the no effect interface this number is 20) and then multiplying the result by 100.

Number of participants in every interface is presented in 4.1.

No effect	20
Explanations	20
Position effect	20
Decoy effect(order: unhealthy, decoy, healthy)	20
Decoy effect(order: decoy, unhealthy, healthy)	20
Decoy effect(order: decoy, healthy, unhealthy)	19
Decoy + position effect	21
Explanations + decoy effect	21
Explanations + position effect	20
Decoy + position + explanations	21

Table 4.1: Number of participants in interfaces

### 4.1 General Data

For Recipe 1, 138 participants chose the healthy one (68.32%), 23 chose the decoy one (11.39%), and 41 chose the unhealthy one (20.3%).

For Recipe 2, 120 participants chose the healthy one (59.41%), 22 chose the decoy one (10.9%), and 60 chose the unhealthy one (29.7%).

For Recipe 3, 112 participants chose the healthy one (55.45%), 33 chose the decoy one (16.34%), and 57 chose the unhealthy one (28.22%).

For Recipe 4, 124 participants chose the healthy one (61.39%), 12 chose the decoy one (5.94%), and 66 chose the unhealthy one (32.67%).

For Recipe 5, 100 participants chose the healthy one (49.5%), 34 chose the decoy one (16.83%), and 68 chose the unhealthy one (33.66%).

For Recipe 6, 103 participants chose the healthy one (50.1%), 37 chose the decoy one (18.3%), and 62 chose the unhealthy one (30.6%).

This also means that 57.5% of all answers were healthy options, 13.2% were decoy options, and 29.3% were unhealthy options.

## 4.2 Hypotheses

In this section, the correctness of all hypotheses is presented together with a graphic representation and statistical significance result (Fisher's ExactTest). When the p-value is below the significance level (in this case, 0.05), the results are statistically significant. For tests that include the decoy effect interface, we used the data from the one that achieved the most significant result (Decoy 1).

### 4.2.1 Hypothesis 1

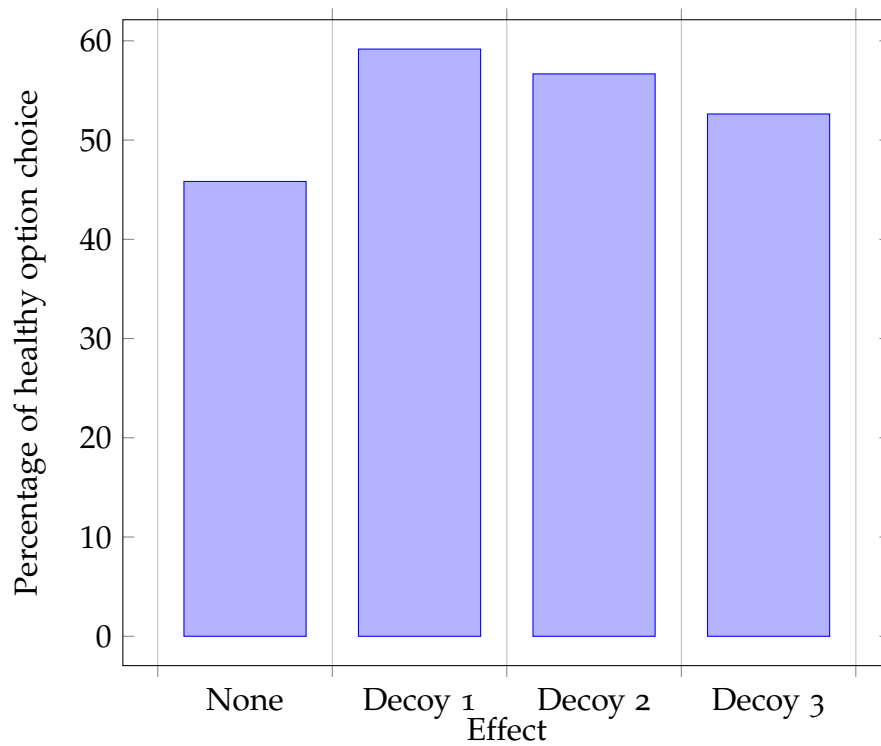
H1: Decoy effect will increase the choice of the target item (healthy recipe). We have used the decoy effect in three different interfaces depending on the order of items. The choice of the target item has increased in each of those three interfaces.

In the interface with no effect, the percentage of healthy option choices was 45.83%, while in the interface with decoy effect and order: unhealthy, decoy, healthy (Decoy 1), the rate of healthy option choices was 59.17%, in the interface with decoy effect and order: decoy, unhealthy, healthy (Decoy 2), the percentage of healthy option choices was 56.67%, and in the interface with decoy effect and order: decoy, healthy, unhealthy (Decoy 3), the rate of healthy option choices was 52.63%.

This proves that the decoy item as a middle item has the most substantial impact on the user.

#### 4 Discussion and Evaluation

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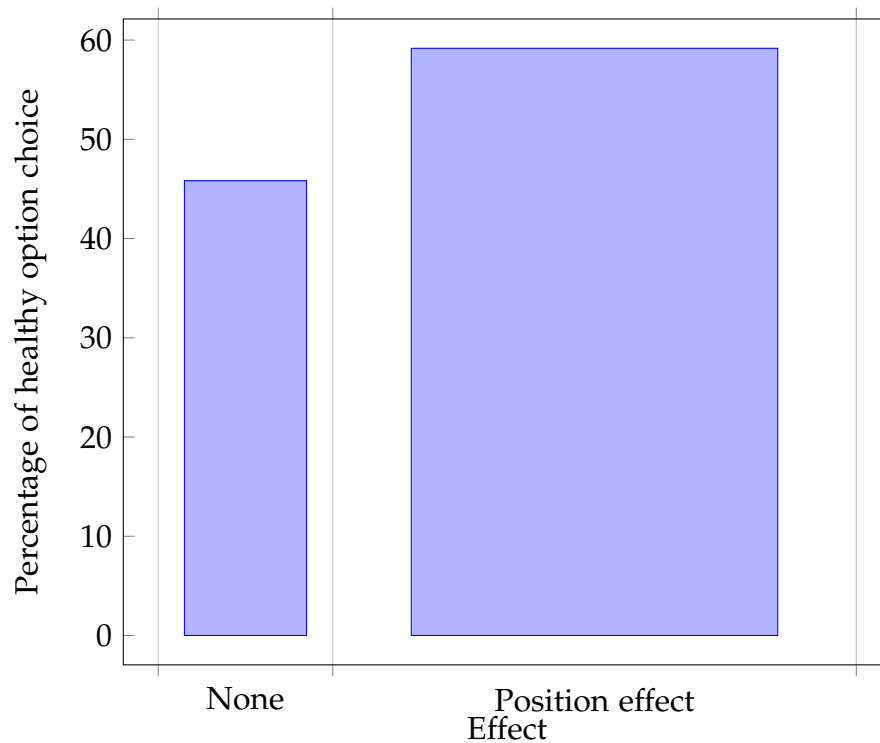


Fisher's ExactTest, one-sided (assuming that the decoy effect interface had more healthy choices than the no effect interface):  $p = 0.0523$   
The p-value is not below the significance level (0.05), so we reject the H1.

### 4.2.2 Hypothesis 2

H2: The position effect will increase the choice of the target item (healthy recipe).

In the interface with no effect, the percentage of healthy option choices was 45.83%, while in the interface with position effect, the rate of healthy option choices was 59.17%.



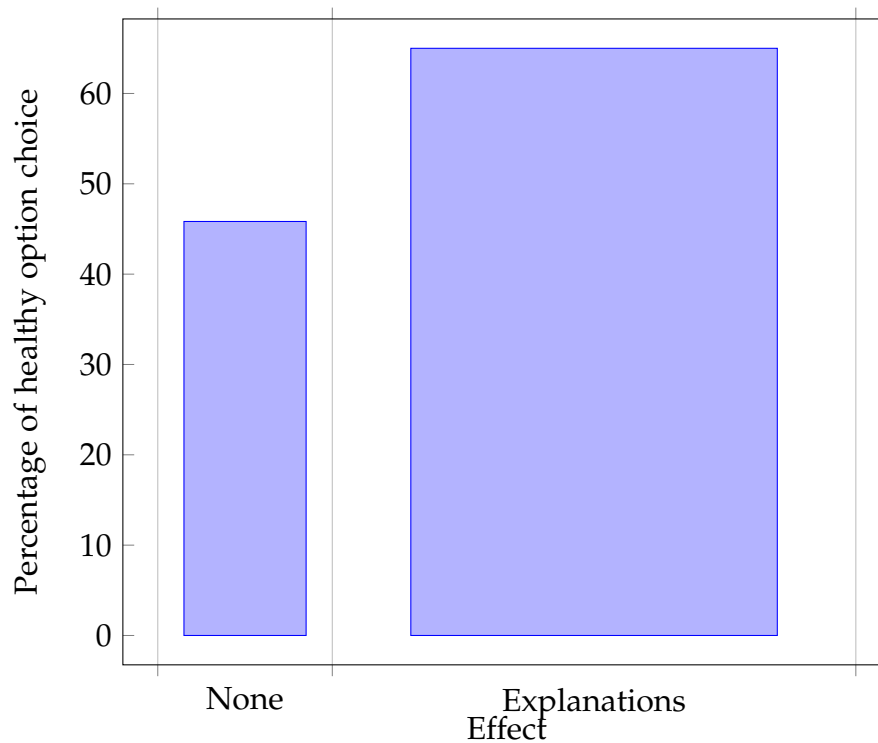
Fisher's ExactTest, one-sided (assuming that the position effect interface had more healthy choices than the no effect interface):  $p = 0.0523$

The p-value is not below the significance level (0.05), so we reject the H2.

### 4.2.3 Hypothesis 3

H<sub>3</sub>: Explanations will increase the choice of the target item (healthy recipe).

In the interface with no effect, the percentage of healthy option choices was 45.83%, while in the interface with explanations, the rate of healthy option choices was 65%.



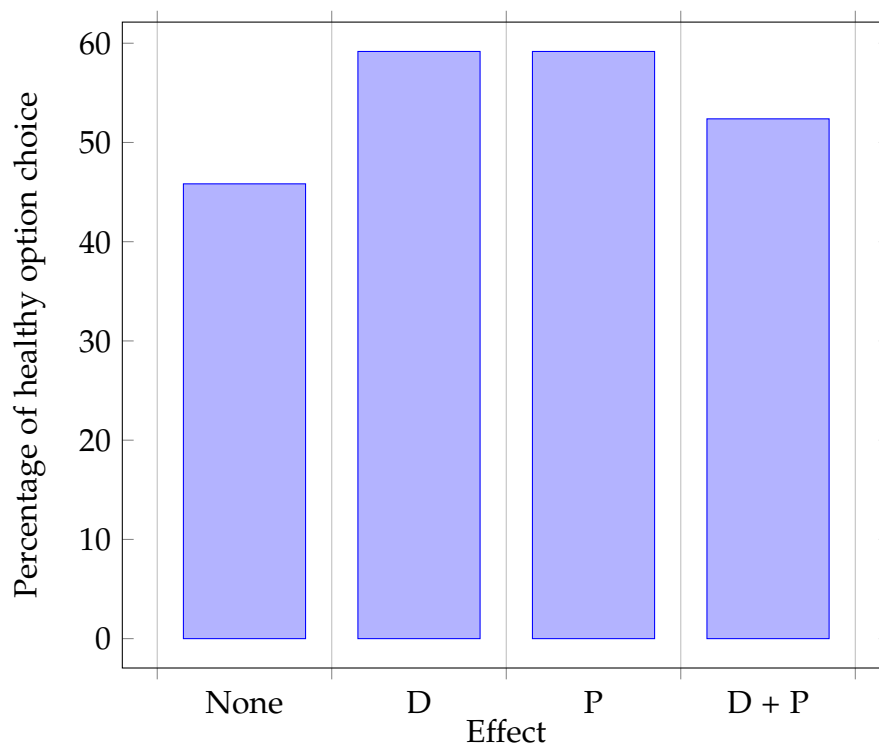
Fisher's ExactTest, one-sided (assuming that the explanations interface had more healthy choices than the no effect interface):  $p = 0.0042$

The p-value is below the significance level (0.05), proving H<sub>3</sub> true.

#### 4.2.4 Hypothesis 4

H<sub>4</sub>: Decoy and position effects in combination will increase the choice of the target item (healthy recipe) more than they did individually.

In the interface with the decoy effect, the percentage of healthy option choices was 59.17% (the highest score of three different decoy interfaces). Also, in the interface with the position effect, the rate of healthy option choices was 59.17%. The combination of these two effects has 52.38% of healthy option choices, proving H<sub>4</sub> false. This shows us that the combination of these two effects reduces their impact since it is lower than the effects individually.



Fisher's ExactTest, one-sided (assuming that the decoy and position effect interface had more healthy choices than the no effect interface):  $p = 0.311$

Fisher's ExactTest, one-sided (assuming that the decoy and position effect interface had more healthy choices than the decoy effect interface):  $p = 0.3061$

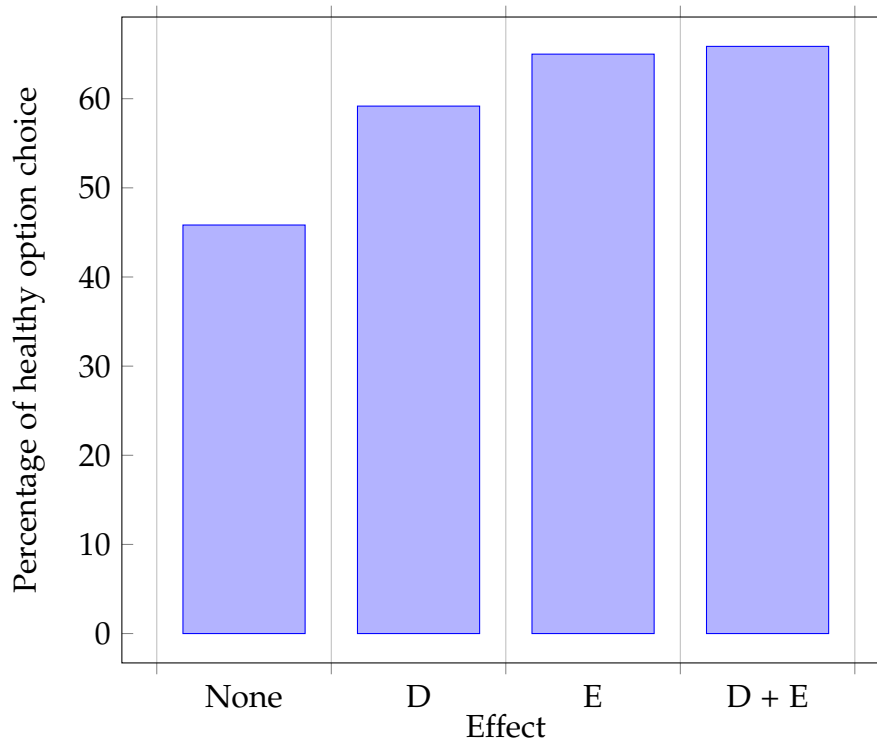
Fisher's ExactTest, one-sided (assuming that the decoy and position effect interface had more healthy choices than the position effect interface):  $p = 0.3061$

The p-value is not below the significance level (0.05), so we reject the H<sub>4</sub>.

### 4.2.5 Hypothesis 5

H5: Decoy effect and explanations in combination will increase the choice of the target item (healthy recipe) more than they did individually.

In the interface with the decoy effect, the percentage of healthy option choices was 59.17% (the highest score of three different decoy interfaces). In contrast, in the interface with explanations, the rate of healthy option choices was 65%. The combination of these two effects has 65.87% of healthy option choices.



Fisher's ExactTest, one-sided (assuming that the decoy effect and explanations interface had more healthy choices than the no effect interface):  $p = 0.0004$

Fisher's ExactTest, one-sided (assuming that the decoy effect and explanations interface had more healthy choices than the explanations interface):  $p = 0.1385$

Fisher's ExactTest, one-sided: (assuming that the decoy effect and explanations interface had more healthy choices than the decoy effect interface)  $p = 0.5828$

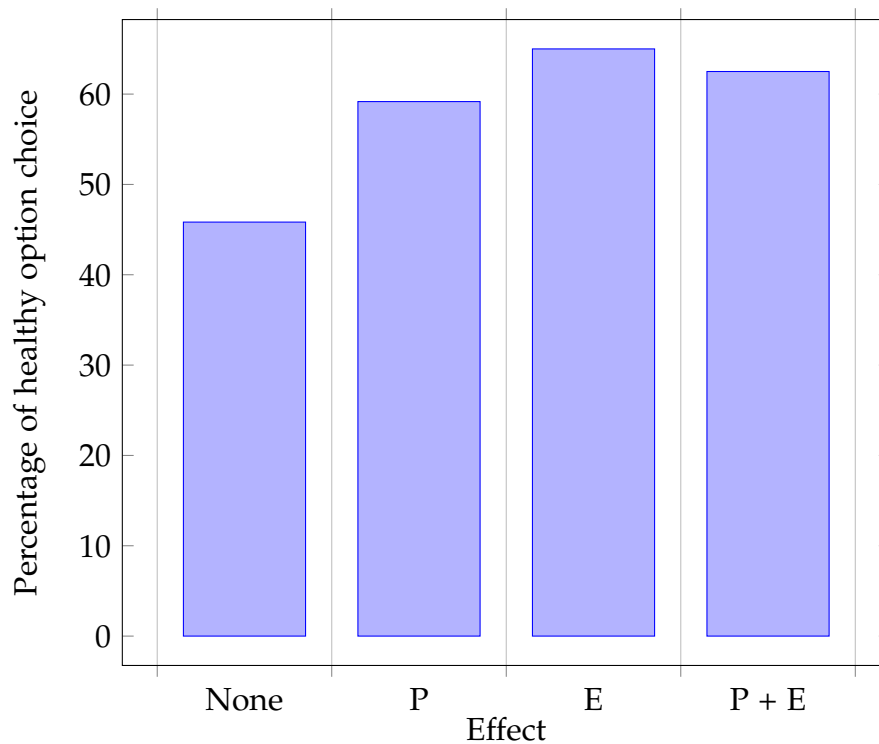
The p-value is not below the significance level (0.05), so we reject H5.



### 4.2.6 Hypothesis 6

H6: Explanations and position effect in combination will increase the choice of the target item (healthy recipe) more than they did individually.

In the interface with the position effect, the percentage of healthy option choices was 59.17%, while in the interface with explanations, the rate of healthy option choices was 65%. The combination of these two effects has 62.5% of healthy option choices, proving H6 false. This result shows us again that the position effect is not good for combining with other effects.



Fisher's ExactTest, one-sided (assuming that the position effect and explanations interface had more healthy choices than the no effect interface):  $p = 0.0137$

Fisher's ExactTest, one-sided (assuming that the position effect and explanations interface had more healthy choices than the explanations interface):  $p = 0.7884$

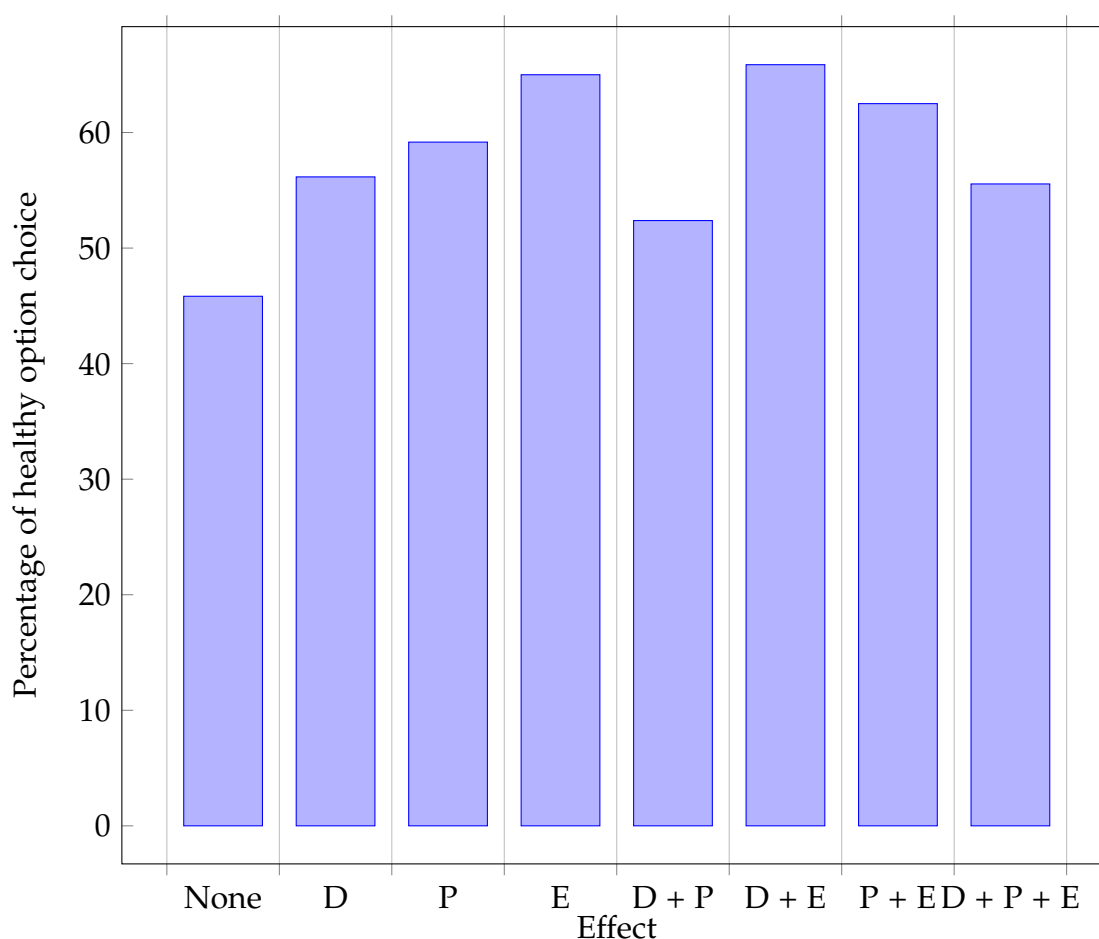
Fisher's ExactTest, one-sided: (assuming that the position effect and explanations interface had more healthy choices than the position effect interface)  $p = 0.6917$

The p-value is not below the significance level (0.05), so we reject H6.

### 4.2.7 Hypothesis 7

H7: Decoy effect, position effect, and explanations in combination will increase the choice of the target item (healthy recipe) more than they did individually and more when only two of them were combined.

The combination of all three effects has 55.55% of healthy option choices, which is less than the combination of explanations and position effect, the combination of decoy effect and explanations, and all the effects individually, proving H7 false. This combination has the lowest impact of all of the combinations in this survey, which proves that participants got more confused when nudged with more effects at the same time.



Fisher's ExactTest, one-sided (assuming that the position effect, decoy effect, and explanations interface had more healthy choices than the no effect interface):  $p = 0.1604$

Fisher's ExactTest, one-sided (assuming that the position effect, decoy effect, and explanations interface had more healthy choices than the position effect interface):  $p = 0.6071$

Fisher's ExactTest, one-sided (assuming that the position effect, decoy effect, and explanations interface had more healthy choices than the explanations interface):  $p = 0.1522$

Fisher's ExactTest, one-sided (assuming that the position effect, decoy effect, and explanations interface had more healthy choices than the decoy effect interface):  $p = 0.6071$

Fisher's ExactTest, one-sided (assuming that the position effect, decoy effect, and explanations interface had more healthy choices than the explanations and decoy effect interface):  $p = 0.0352$

Fisher's ExactTest, one-sided (assuming that the position effect, decoy effect, and explanations interface had more healthy choices than the explanations and position effect interface):  $p = 0.3005$

Fisher's ExactTest, one-sided (assuming that the position effect, decoy effect, and explanations interface had more healthy choices than the position and decoy effect interface):  $p = 0.7047$

The p-value is not below the significance level (0.05), so we reject H7.

### 4.3 Healthy Food Preferences

Of the 138 participants who chose the healthy item in Recipe 1, 79 chose that they prefer to eat healthy food, 57 chose that they prefer to eat healthy food sometimes, and only two didn't.

Of the 120 participants who chose the healthy item in Recipe 2, 69 chose that they prefer to eat healthy food, and 51 chose that they prefer to eat healthy food sometimes.

Of the 112 participants who chose the healthy item in Recipe 3, 61 chose that they prefer to eat healthy food, 50 chose that they prefer to eat healthy food sometimes, and only one didn't.

Of the 124 participants who chose the healthy item in Recipe 4, 67 chose that they prefer to eat healthy food, 56 chose that they prefer to eat healthy food sometimes, and only one didn't.

Of the 100 participants who chose the healthy item in Recipe 5, 59 chose that they prefer to eat healthy food, and 41 chose that they prefer to eat healthy food sometimes.

Of the 103 participants who chose the healthy item in Recipe 6, 59 of them chose that they prefer to eat healthy food, 42 chose that they prefer to eat healthy food sometimes, and only two didn't.

Table 4.2: Healthy Food Preferences

Preference	Prefers	Prefers sometimes	Doesn't prefer
Recipe 1	79	57	2
Recipe 2	69	51	0
Recipe 3	61	50	1
Recipe 4	67	56	1
Recipe 5	59	41	0
Recipe 6	59	42	2

## 4.4 Users' satisfaction and importance of healthiness

After concluding the survey, every participant had to answer two questions about the survey. The questions were "How important was the aspect of healthiness for your final choice" and "How well did the food recommendations include food items you like" Participants could choose a number between one and five where one stands for "not important at all" and five stands for "very important".

The average importance of healthiness in the final choice of participants was 3.57, and the average satisfaction was 3.44. The satisfaction of participants also affected their choices, in the sense that some other healthy alternatives would be more chosen by some participants. Additionally, various intolerances or allergies to certain foods could have contributed to this choice.

The importance of the aspect of healthiness for the final choice once again confirmed that most of the participants prefer to eat healthy food. Before the survey, participants stated that 93 of them preferred to eat only healthy food (46.04%), 102 preferred to eat healthy sometimes (50.5%), and only 7 of them didn't prefer eating healthy food (3.46%). This percentage dropped after the survey, where 42 of the participants chose 1 or 2 on the important scale, but still, the highest numbers are in the groups of the participants who chose 4 or 5 (56.44%).

Satisfaction could also have influenced the importance percentage. When participants take into account some other attributes and, in the absence of a healthy choice according to their taste, they choose the unhealthier ones.

Table 4.3: Users' satisfaction and importance of healthiness

	Importance	Satisfaction
1	9(4.46%)	20(9.9%)
2	33(16.34%)	42(20.8%)
3	46(22.77%)	26(12.87%)
4	<b>62(30.69%)</b>	<b>57(28.22%)</b>
5	52(25.74%)	<b>57(28.22%)</b>

Average importance: 3.57

Average satisfaction: 3.44

## 4.5 Users' satisfaction

Of the 138 participants who chose the healthy item in Recipe 1, 48 replied to the question "How well did the food recommendations include food items you like" with 5, 49 replied with 4, 11 replied with 3, 22 replied with 2, and eight replied with 1.

Of the 120 participants who chose the healthy item in Recipe 2, 46 replied to the question "How well did the food recommendations include food items you like" with 5, 40 replied with 4, 9 replied with 3, 17 replied with 2, and eight replied with 1.

Of the 112 participants who chose the healthy item in Recipe 3, 45 replied to the question "How well did the food recommendations include food items you like" with 5, 42 replied with 4, 8 replied with 3, 14 replied with 2, and three replied with 1.

Of the 124 participants who chose the healthy item in Recipe 4, 49 replied to the question "How well did the food recommendations include food items you like" with 5, 45 replied with 4, 11 replied with 3, 18 replied with 2, and one replied with 1.

Of the 100 participants who chose the healthy item in Recipe 5, 41 replied to the question "How well did the food recommendations include food items you like" with 5, 42 replied with 4, three replied with 3, 10 replied with 2, and four replied with 1.

Of the 103 participants who chose the healthy item in Recipe 6, 43 replied to the question "How well did the food recommendations include food items you like" with 5, 43 replied with 4, two replied with 3, nine replied with 2, and six replied with 1.

Table 4.4: Users' satisfaction

Satisfaction	1	2	3	4	5
Recipe 1	8	22	11	49	48
Recipe 2	8	17	9	40	46
Recipe 3	3	14	8	42	45
Recipe 4	1	18	11	45	49
Recipe 5	4	10	3	42	41
Recipe 6	6	9	2	43	43

## 4.6 The importance of the aspect of healthiness

Of the 138 participants who chose the healthy item in Recipe 1, 47 replied to the question "How important was the aspect of healthiness for your final choice" with 5, 52 replied with 4, 20 replied with 3, 18 replied with 2, and one replied with 1.

Of the 120 participants who chose the healthy item in Recipe 2, 41 replied to the question "How important was the aspect of healthiness for your final choice" with 5, 45 replied with 4, 17 replied with 3, and 17 replied with 2.

Of the 112 participants who chose the healthy item in Recipe 3, 43 replied to the question "How important was the aspect of healthiness for your final choice" with 5, 40 replied with 4, 14 replied with 3, and 15 replied with 2.

Of the 124 participants who chose the healthy item in Recipe 4, 45 replied to the question "How important was the aspect of healthiness for your final choice" with 5, 42 replied with 4, 17 replied with 3, 17 replied with 2, and three replied with 1.

Of the 100 participants who chose the healthy item in Recipe 5, 40 replied to the question "How important was the aspect of healthiness for your final choice" with 5, 52 replied with 4, and eight replied with 3.

Of the 103 participants who chose the healthy item in Recipe 6, 48 replied to the question "How important was the aspect of healthiness for your final choice" with 5, 47 replied with 4, six replied with 2, and two replied with 1.

Table 4.5: The importance of the aspect of healthiness

Importance	1	2	3	4	5
Recipe 1	1	18	20	52	47
Recipe 2	0	17	17	45	41
Recipe 3	0	15	14	40	43
Recipe 4	3	17	17	42	45
Recipe 5	0	0	8	52	40
Recipe 6	2	6	0	47	48

In this section, we run the One-way Analysis of Variance (ANOVA) test to determine whether a relationship exists between the importance of the aspect of healthiness and choosing the healthy option. When the p-value is below the significance level (in this case, 0.05), the results are statistically significant.

With  $p = 0.00001$ , it is shown that the importance of the aspect of healthiness of the participant has a significant relationship with their choice of the healthy option.

#### 4 Discussion and Evaluation

Table 4.6: No effect

Option	Recipe 1	Recipe 2	Recipe 3	Recipe 4	Recipe 5	Recipe 6
Healthy	<b>10(50%)</b>	9(45%)	9(45%)	9(45%)	8(40%)	<b>10(50%)</b>
Unhealthy	<b>10(50%)</b>	<b>11(55%)</b>	<b>11(55%)</b>	<b>11(55%)</b>	<b>12(60%)</b>	<b>10(50%)</b>

Rate of healthy option choices: 45.83%

Table 4.7: Explanations

Option	Recipe 1	Recipe 2	Recipe 3	Recipe 4	Recipe 5	Recipe 6
Healthy	<b>15(75%)</b>	<b>12(60%)</b>	<b>11(55%)</b>	<b>17(85%)</b>	<b>13(65%)</b>	<b>10(50%)</b>
Unhealthy	5(25%)	8(40%)	9(45%)	3(15%)	7(35%)	<b>10(50%)</b>

Rate of healthy option choices: 65%

Table 4.8: Position effect

Option	Recipe 1	Recipe 2	Recipe 3	Recipe 4	Recipe 5	Recipe 6
Healthy	<b>14(70%)</b>	<b>12(60%)</b>	<b>13(65%)</b>	<b>12(60%)</b>	7(35%)	<b>13(65%)</b>
Unhealthy	6(30%)	8(40%)	7(35%)	8(40%)	<b>13(65%)</b>	7(35%)

Rate of healthy option choices: 59.17%

Table 4.9: Decoy effect(order: unhealthy, decoy, healthy)

Option	Recipe 1	Recipe 2	Recipe 3	Recipe 4	Recipe 5	Recipe 6
Healthy	<b>14(70%)</b>	<b>15(75%)</b>	<b>10(50%)</b>	<b>14(70%)</b>	<b>10(50%)</b>	<b>8(40%)</b>
Decoy	4(20%)	0(0%)	7(35%)	2(10%)	4(20%)	7(35%)
Unhealthy	2(10%)	5(25%)	3(15%)	4(20%)	6(30%)	5(25%)

Rate of healthy option choices: 59.17%

Table 4.10: Decoy + position effect

Option	Recipe 1	Recipe 2	Recipe 3	Recipe 4	Recipe 5	Recipe 6
Healthy	<b>14(66.66%)</b>	8(38.1%)	<b>9(42.86%)</b>	<b>17(80.95%)</b>	7(33.33%)	<b>11(52.38%)</b>
Decoy	5(23.8%)	<b>11(52.38%)</b>	<b>9(42.86%)</b>	0(0%)	<b>9(42.86%)</b>	9(42.86%)
Unhealthy	2(9.52%)	2(9.52%)	3(14.28%)	4(21.05%)	5(23.8%)	1(4.76%)

Rate of healthy option choices: 52.38%



#### 4.6 The importance of the aspect of healthiness

Table 4.11: Decoy + position + explanations

Option	Recipe 1	Recipe 2	Recipe 3	Recipe 4	Recipe 5	Recipe 6
Healthy	<b>14(66.66%)</b>	<b>11(52.38%)</b>	<b>10(47.62%)</b>	<b>13(61.9%)</b>	<b>12(57.14%)</b>	<b>10(47.62%)</b>
Decoy	5(23.8%)	8(38.1%)	5(23.8%)	3(14.29%)	8(38.1%)	6(28.57%)
Unhealthy	2(9.52%)	2(9.52%)	6(28.57%)	5(23.8%)	1(4.76%)	5(23.8%)

Rate of healthy option choices: 55.55%

Table 4.12: Explanations + decoy effect

Option	Recipe 1	Recipe 2	Recipe 3	Recipe 4	Recipe 5	Recipe 6
Healthy	<b>14(66.66%)</b>	<b>15(71.43%)</b>	<b>12(57.14%)</b>	<b>16(76.19%)</b>	<b>14(66.66%)</b>	<b>12(57.14%)</b>
Decoy	5(23.8%)	2(9.52%)	8(38.1%)	3(14.29%)	3(14.29%)	6(28.57%)
Unhealthy	2(9.52%)	4(19.05%)	1(4.76%)	2(9.52%)	4(19.05%)	3(14.29%)

Rate of healthy option choices: 65.87%

Table 4.13: Explanations + position effect

Option	Recipe 1	Recipe 2	Recipe 3	Recipe 4	Recipe 5	Recipe 6
Healthy	<b>16(80%)</b>	<b>16(80%)</b>	<b>12(60%)</b>	9(45%)	<b>12(60%)</b>	<b>10(50%)</b>
Unhealthy	4(20%)	4(20%)	8(40%)	<b>11(55%)</b>	8(40%)	<b>10(50%)</b>

Rate of healthy option choices: 62.5%

Table 4.14: Decoy effect(order: decoy, unhealthy, healthy)

Option	Recipe 1	Recipe 2	Recipe 3	Recipe 4	Recipe 5	Recipe 6
Healthy	<b>14(70%)</b>	<b>14(70%)</b>	<b>13(65%)</b>	7(35%)	<b>9(45%)</b>	<b>11(55%)</b>
Decoy	1(5%)	0(0%)	4(20%)	3(15%)	4(20%)	4(20%)
Unhealthy	5(25%)	6(30%)	3(15%)	<b>10(50%)</b>	7(35%)	5(25%)

Rate of healthy option choices: 56.67%

Table 4.15: Decoy effect(order: decoy, healthy, unhealthy)

Option	Recipe 1	Recipe 2	Recipe 3	Recipe 4	Recipe 5	Recipe 6
Healthy	<b>13(68.42%)</b>	8(42.1%)	<b>13(68.42%)</b>	<b>10(52.63%)</b>	<b>8(42.1%)</b>	<b>8(42.1%)</b>
Decoy	3(15.79%)	1(5.27%)	0(0%)	1(5.27%)	6(31.58)	5(26.32%)
Unhealthy	3(15.79%)	<b>10(52.63%)</b>	6(31.58)%	8(42.1%)	5(26.32%)	6(31.58)%

Rate of healthy option choices: 52.63%



## 5 Conclusion and Future Work

This thesis focused on the analysis of three different decision biases, their theoretical background, research that has already been done on this topic, and conducting a survey that confirmed the significant role that these biases have in Food Recommender Systems.

### 5.1 Survey

For this paper, a survey in the form of a web application was created. Participants were randomly assigned to one of the interfaces where they had to choose some of the recipes offered to them. In these interfaces, some participants were exposed to the influence of the decoy effect, position effect, explanations, or combinations of these effects to measure the best result. The most decisive influence had the combination of decoy effect and explanations (65.17% of healthy choices), then explanations (65%), and explanations and position effect (62.5%). This shows us a significant advantage of explanations over other effects. Also, all interfaces that gave statistically significant results after the Fisher's Exact test contained explanations. There were only three such interfaces: Explanations interface, Explanations and Decoy effect interface, and Explanations and Position effect interface. The last two interfaces had a significant result only compared to the interface without effects, while the results compared to interfaces with these effects individually were not significant.

The small number of different options (only three) prevented the significant success of the position effect, which is normally achieved with large amounts of data. The decoy effect without presented nutritional values did not show the participants a clear enough difference between the healthiness of the recipes. For this reason, explanations had the best success, because they clearly separated healthy from unhealthy options, and, as we learned from the survey, most of the participants were looking for healthier options.

The combination of all three effects did not achieve significant results (55.55%), proving that users can get confused when exposed to more than two different effects. Additionally, only one of the three combinations of two effects had better impact than those effects individually which proves to us that the effects are not enhanced by combining.

### 5.2 Future Work

The first limitation of the survey was that, among the participants, there were only seven of them who didn't prefer healthy food. Although significant progress has been made, there were not enough participants from the target group. A possible improvement would be testing more participants with more recipes to improve the overall satisfaction of the participants with the recipes, which was 3.44/5 in this survey.

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