Kristiania

Digitalization, Companies, and Consumers

Investigating Digitalized Healthy Food Labels and Consumer Behavior

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Digitalization, Companies, and Consumers: Investigating Digitalized Healthy Food Labels and Consumer Behavior

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Acknowledgment

Undertaking a Ph.D. is very intellectually stimulating, but also a difficult task. I had a clear idea about what I would research. However, this changed when I was introduced to other research domains. One type of intellectual activity involves analyzing a complex problem by breaking it into simpler units and investigating their relationship. Another approach uses synthesis, which involves building new knowledge based on prior knowledge. Although I have had experience with both, it was particularly challenging when I came from one research domain to others that do not have the same ontological, epistemological, and axiological positions. In these situations, the lines between analysis and synthesis become fuzzier. However, new knowledge is highly likely to emerge in these situations, and this thesis is a product of such a situation. Several people have encouraged me during these tasks, and I would like to thank them.

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Sammendrag

Usunn matkonsum er et betraktelig problem og flere tidligere strategier har blitt utprøvd for å adressere dette problemet. Usunn matkonsum har en negativ påvirkning for samfunnet helhetlig, bedrifter, og forbrukere. Tidligere strategier innebærer reguleringer, skating, subsidiering, dulting, markedsføring, og merkeordinger for sunn mat. Merkeordninger for sunn mat er symboler og logoer som signaliserer til forbrukere hvor sunn et produkt er, enten ved evaluering av hvor sunn produktet er helhetlig, dets spesifikke næringsinnhold, eller en kombinasjon av begge. Sunn matmerkning kan bli ansett som både et informasjonssystem problem og et atferdsvitenskapelig problem, der hvor data er redusert til informasjon som adresserer et praktisk problem. Slik transformering påvirker også forbrukeratferd, som fører til atferdsendring. En tilnærming er å kombinere litteratur fra digitaliseringsprosesser og forbrukeratferdsanalyse. Digitaliserte sunn matmerking kan være en strategi som kan hjelpe forbrukere å velge sunnere produkter ved å presentere nye og engasjerende merker ved bruk av digital teknologier. Denne avhandlingen utforsker hvordan digitaliserte sunn matmerking påvirker forbrukeratferd på flere måter. For det første, et systematisk gjennomgangsstudie som undersøkte klassifikasjonen av digitalisert sunn matmerking og undersøkte tidligere forskning på dets påvirkning på forbrukeratferd. For det andre, en valg-basert konjunkt eksperiment ble brukt for å undersøke hvordan enkelte merker kunne øke mat valg og undersøkte hvorvidt noen av disse var mer hjelpsom for impulsive forbrukere. For det tredje, en konseptuell studie ble gjort for å undersøkte hvordan disse merkene blir utviklet og implementert av bedrifter og hvordan de er formet av forbrukeres atferd. Til slutt, en vurderings-basert konjunkt eksperiment ble brukt for å undersøke hvordan

forbrukere reagerer på noen av disse merkene når symboler og logoer er definert fra dem selv, fra detaljhandlere, og offentlig politiske tiltak. Denne avhandlingen bidrar til at digitalisert sunn matmerking og deres påvirkning på forbrukeratferd kan bli forstått gjennom informasjonssystem og atferdsvitenskap perspektiver, særlig gjennom i kontekst av digitalisering og forbrukeratferdsanalyse. Bidraget til de individuelle studiene er at enkelte av disse digitaliserte sunn matmerkignssytemer er mer effektive enn andre, der enkelte forbrukere foretrekker merkesystemer basert på deres tidligere kjøp ovenfor en rabatt-basert merking, bedrifter kan få mer innsikt i forbrukeratferd, og sunn matmerking som er basert på forbrukernes egne definisjoner er foretrukket over andre kilder. Implikasjonene av denne forskningen er at slike merker kan bidra til forbrukere, bedrifter, og samfunnet med verdi. Når det gjelder fremtidig arbeid, så foreslås det en bredere konseptualisering når det gjelder digitaliseringsprosesser og forbrukeratferd.

Abstract

Unhealthy food consumption is a significant problem, and several previous strategies have been attempted to address this issue. Unhealthy food consumption has a negative impact on society as a whole, companies, and consumers. Previous strategies have included regulations, taxation, subsidization, nudging, marketing, and front-of-packaging labeling of healthy food products. Front-of-package food labeling is symbols or logos that signal to consumers how healthy a product is, either by evaluating its overall health, specific nutrients, or a combination of both. Healthy food labeling can be viewed as both an information systems problem and a behavioral sciences problem, as it transforms data into information that addresses a practical issue. Such transformations also impact consumer behavior, leading to behavioral change. One approach to this is to combine literature from digitalization processes and consumer behavior analysis. Digitalized healthy food labeling could be one strategy to help consumers choose healthier products by presenting novel and engaging labels using digital technologies. This thesis explores how digitalized healthy food labels impact consumer behavior in several ways. First, a systematic review investigated the classification of digitalized food labeling and examined previous research on its impact on consumer behavior. Second, a choice-based conjoint experiment was used to investigate how some labels could increase food choices and examine whether some were more helpful for impulsive consumers. Third, a conceptual study was used to investigate how these labels could be developed and implemented by companies and how they are shaped by consumers' behavior. Finally, a rating-based conjoint experiment was used to investigate how consumers react to some of these labels when such symbols or logos are defined by themselves, by

retailers, or by public policy measures. The contribution of this thesis is that digitalized healthy food labels and their impact on consumer behavior can be understood through information systems and behavioral science perspectives, particularly in the context of digitalization and consumer behavior analysis. The contribution of the individual studies are that some of these digitalized healthy food labels may be more effective than others, some consumers prefer labeling systems based on their past purchases over a discount-based labeling, companies may gain more insights into consumer behavior, and that healthy food labels which are based on consumers own definitions are preferred over other sources. The implications of this research are that such labels could provide consumers, companies, and society with value. For future work, a broader conceptualization related to digitalization processes and consumer behavior is also proposed.

Content

List of attachments

Ljusic, N., Fagerstrøm, A., Pawar, S., & Arntzen, E. (2022). Effects of digitalized front-of-package food labels on healthy food-related behavior: a systematic review. *Behavioral Sciences*, *12*(10), 363.

Ljusic, N., Fagerstrøm, A., Sigurdsson, V., & Arntzen, E. (2023). Information, ingestion, and impulsivity: The impact of technology-enabled healthy food labels on online grocery shopping in impulsive and non-impulsive consumers. *Frontiers in Nutrition*, *10*, 1129883.

Ljusic, N., Fagerstrøm, A., & Arntzen, E., (in press) Technology-Enabled Healthy Food Labels in the Interaction Between the Marketing Firm and Consumer. In *The Marketing Firm, Volume II.* Palgrave Macmillan.

Ljusic, N., Fagerstrøm, A., & Arntzen, E., (n.d.) What Does "Healthy" Mean, Anyway? The Impact of Public Policy, and Retailer, and Consumer Self-Generated Labels on Online Grocery Shopping.

1 INTRODUCTION

1.1 The Topic of this Thesis

The topic of this thesis is the phenomenon of digitalization of healthy food labels and their impact on consumer behavior. The context of this thesis is that unhealthy food consumption is problematic for society, companies, and consumers. Several previous solutions exist, ranging from hard to soft strategies (Vecchio & Cavallo, 2019). However, these problems still exist (World Health Organization, 2024), which suggests that more research is needed on this topic. Numerous ways exist to transform data into information (Rainer & Prince, 2021), and more information about the nutritional value of food products does not necessarily increase healthy food preferences in consumers (Ikonen et al., 2020; Temple, 2020). However, some information may increase healthy food preference in consumers if it is provided in the right amount, at the right time, and to the right person. Building on this, some have suggested presenting front-of-package food labels, simplified symbols, or logos that signal to consumers how healthy a product is (World Health Organization, 2004, 2019). In parallel, several retail technologies are emerging that can provide value to companies and consumers (Inman & Nikolova, 2017; Shankar et al., 2021). One strategy is to use digital technologies (Bharadwaj et al., 2013) and present novel food labeling systems to consumers. Companies that undergo digitalization (Verhoef et al., 2021) may present novel information to consumers, which may increase consumers' healthy food preferences. More specifically, such food labels can be digitalized to provide novel information to consumers.

This thesis argues for two central claims and suggests two important points related to future empirical research. First, digitalized healthy food labels may be classified in terms of different aspects related to digitalization. These are termed digitalized static, interactive, and technology-enabled labels. Second, consumers' behavior toward digitalized healthy food labels is impacted by their antecedent events and the variables that moderate these. For instance, instructions related to the products or labeling systems, sources of such instructions, or consumers' preference for immediate vs delayed benefits may moderate the impact of such labels. Third, an online grocery store's decision to implement or develop digitalized healthy food labels is shaped by consumers' behaviors, and consumers react differently to different labels provided by a company. Specifically, a company's behavior is also impacted by antecedent events and the consequences that consumers give. These interactions may result in consumers obtaining the information they want about a company's products, and companies may gain insights into changing preferences of consumer behavior by using these labels. Lastly, an analysis of how consumers shape a company's digitalization processes at a broader level is suggested for future work. The support for these claims will be based on this introductory chapter and the papers of this thesis.

1.2 The Purpose of this Thesis

The purpose of this thesis is to investigate how digitalized healthy food labels change consumer behavior. It is based on aspects related to practical problems of unhealthy food consumption and advances the academic literature. These digitalized healthy food labels may benefit consumers, companies, and society. Regarding the practical problems concerning unhealthy food consumption, consumers often state that they want to eat healthier, but their behavior does not always align with what they state. Furthermore, consuming healthier products is associated with numerous benefits, such as the absence of disease, longer life, higher energy levels, better skin and dental health, and even better mental health. In essence, these benefits may contribute to overall consumer well-being. Second, companies may gain several benefits by using these labels. They may profit by selling more products and avoiding negative reputations, but also gain more insights into consumer behavior. As digitalization processes are becoming more common in many aspects of our world, companies must understand what drives consumer behavior in digital contexts. Companies that do not adapt to changing consumer behavior and preferences cannot deliver offers that consumers need and want. These digitalized healthy food labels may also be a source for companies to map out these changing consumer choices and preferences. Lastly, society as a whole would benefit from individuals consuming healthier products. This could reduce the economic costs associated with treating people who are obese and the lack of productivity associated with unhealthy food consumption. Regarding advancement in the academic literature, several topics have received relatively little attention compared to physical healthy food labeling. These include classification regarding digitalized front-of-package food labels, how certain digitalized healthy food labels may help vulnerable consumers make better food decisions, understanding companies' decisions to implement novel digitalized healthy food labels, and providing personalized labeling of healthy foods based on consumers' definitions.

1.3 The Scope of the Thesis

The scope of this thesis is interdisciplinary, encompassing several research fields, conceptualizations, and key terms, as illustrated in Figure 1 and Table 1. Research disciplines and phenomena can be identified by what they study or where they look for their explanations or causes (Vargas, 2014); that is, by the dependent and independent variables they study. This thesis investigates the impact of digitalized healthy food labels on consumer behavior. Consumer behavior is broadly referred to as behavior related to the acquisition, usage, and disposal of products and services with value (Holbrook, 1987). In this thesis, digitalized healthy food labels are defined as any symbols or logos that signal to consumers how healthy a food product is based on information provided by digital technologies in online grocery store settings. They are healthy food labels presented using a digital medium or device and placed in the point of purchase situations. This was chosen based on the overall research question, the scope of this work, background knowledge, the conceptual framework provided, and the contribution of this thesis.

Table 1

Term Definitions

Term	Definition	Source
Information systems	Information systems can be defined "*as a system that collects, processes, stores, analyzes, and disseminates information for a specific purpose*" (Rainer & Prince, 2021, p. 4). Information systems as a research discipline is the study of such systems.	(Rainer & Prince, 2021; Stair & Reynolds, 2018)
Healthy food labeling	Healthy food labeling can be defined as any use of logos or symbols that simplify data about food products to convey information regarding aspects related to healthy food. Consumer behavior is impacted by how these labeling systems are described or explained to them.	See "Information systems," "Front-of-package food labeling," and "Consumer behavior"
Front-of-package food labeling	Front-of-package food labeling can be defined as healthy food labels that convey information on whether the products are healthy overall (summary	(Hersey et al., 2013; Ikonen et al., 2020; Temple, 2020; World Health Organization, 2019)

	labels), based on their individual nutrients (nutrient-specific labels), or a combination of these two (combined labels). It is a type of healthy food labeling.	
Information technology	Information technology "*relates to any computer-based tool that people use to work with information and support the information and information processing needs of an organization* (Rainer & Prince, 2021, p. 12)." It can be described by its hardware, software, databases, networks, procedures, and the people using them.	(Rainer & Prince, 2021; Stair & Reynolds, 2018)
Digital technologies	Digital technologies are "*combinations of information, computing, communication, and connectivity technologies* (Bharadwaj et al., 2013, p. 471)" They overlap with information technology, but differ in that these four characteristics are emphasized. Digital technologies provide information and value typically	(Bharadwaj et al., 2013; Wessel et al., 2021)

	beyond company boundaries, through interfirm relations, and in evolving organizations.	
Digitization	Digitization is the conversion of analog information into bit strings (i.e., 1s and 0s).	(Hund et al., 2021)
Digitalization	Digitalization refers to the use of digital technologies to deliver products and services, providing value that extends beyond mere digitization.	(Mergel et al., 2019; Parviainen et al., 2017)
Digital transformation	Digital transformation refers to the use of digital technologies that result in a change to an organization's strategic models. It is "*a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies* (Vial, 2021, p. 13) ."	(Vial, 2021; Wessel et al., 2021)
Digital innovation	Digital innovation is innovation through the use of digital technologies. It is "*the creation or adoption, and*	(Hund et al., 2021)

	exploitation of an inherently unbounded, value-adding novelty (e.g., product, service, process, or business model) through the incorporation of digital technology (Hund et al., 2021, p. 2) ."	
Digitalized healthy food labeling	Digitalized healthy food labeling is the use of simplified logos or symbols that reduce data to information about how healthy a food product is. These labels are presented through digital media (i.e., digital technologies) in point-of-purchase situations at online grocery stores. These labels can be classified as static, interactive, or technology-enabled. These labels overlap with traditional information technology and the four characteristics of digital technologies in the context of interfirm relations.	See "Healthy food labeling" and "Digitalization"
Behavioral sciences	Behavioral sciences can be defined as the study of behavior. Behavior can also be defined as the way	(Cohen et al., 2013; Hallsworth, 2023; Johnston et

	something functions or an interaction between the movement of an organism and its environment.	al., 2010; Merriam-Webster, n.d.)
Consumer behavior	Consumer behavior is behavior related to the acquisition, usage, and disposition of products and services with value.	(Holbrook, 1987)
Consumer behavior analysis	Consumer behavior analysis is the study of how environmental and situational factors influence consumer behavior, drawing on literature from behavior analysis, behavioral economics, and marketing science.	(Foxall, 2016; 2017)
Bilateral contingency	The bilateral contingency model describes how two operant systems interact. An operant system behaves as a function of environmental and situational factors. Bilateral contingencies refer to situations where one operant system provides environmental or situational events to another, depending on the behavior of the	(Foxall, 1999, 2020; 2021)

	latter, and vice versa, leading to reciprocal changes in behavior.	
Three-term contingency	Three-term contingency describes relationships between behavior, consequences, and antecedent events. Consequences are reinforcers or punishers, while antecedent events are discriminative stimuli and motivating operations.	(Catania, 2013; Cooper et al., 2020; Pierce & Cheney, 2017; Skinner, 1953)
Rule-governed behavior	Rule-governed behavior is behavior under the influence of antecedent verbal stimuli referred to as rules (or instructions, descriptions, or explanations). These rules are contingency-specifying, as they describe the relationship between behavior and environment through spoken or written form, and they alter the function of other consequences and antecedent events.	(Pelaez, 2013; Schlinger & Blakely, 1987; Skinner, 1969; Zettle & Hayes, 1982)

Delay discounting	Delay discounting refers to the phenomenon where the subjective value of an outcome decreases as a function of increasing delay to its recipient. When the behavior of an operant system decreases as a function of delay to a greater degree than other behaviors or systems, the behavior or the system is said to be more impulsive than the comparison. It is often studied by investigating the impact of differences in the delay of consequences or through rules on behavior.	(Green & Myerson, 2004; Odum, 2011; Rachlin, 2000)
Digital operant systems perspective	The Digitalized Operant Systems Perspective states that an operant system changes as a function of digital technologies. Data being processed into information is the same as when environmental events that do not change behavior are processed, such that it now changes behavior through presenting consequences and antecedent events. The Digitalized Bilateral Contingency Model states that companies' behavior	See "Digitalization," "Three-term contingency," and "Bilateral Contingency Model"

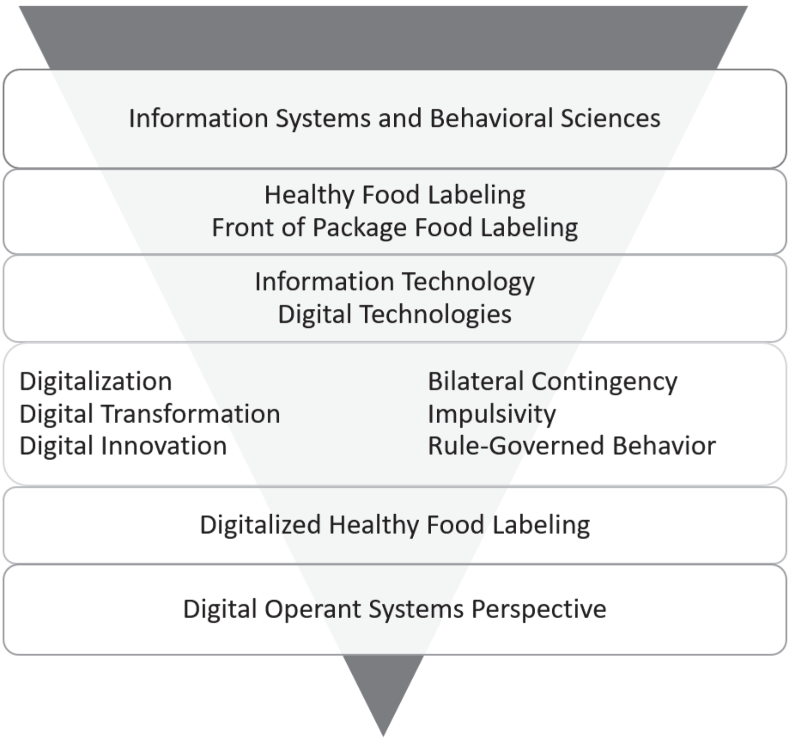
related to digitization, digitalization, digital transformation, and digital innovation is shaped by their environmental events and especially by the users of these digital technologies.

Note. A description of terms, definitions, and sources.

In the broadest terms, this thesis falls under information systems and behavioral sciences, drawing research from front-of-package food labeling, digitalization, and consumer behavior analysis. It falls under information systems and behavioral sciences because it studies how information systems impact behavior to solve practical problems. In the academic field of information systems, an information system is characterized by transforming data into meaningful information for decision-making to solve specific problems (Rainer & Prince, 2021; Stair & Reynolds, 2018). Reducing the complexity of transforming data about food products into information in such a manner that gives value to consumers is an information systems problem. It also highlights how digitalized healthy food labels can be understood with recent perspectives in investigating digitalization by using digital technologies rather than solely using information technology infrastructures and established information systems, and going beyond the traditional information technology-business model alignment view. Behavioral sciences refer to research disciplines that study behavior (Cohen et al., 2013; Hallsworth, 2023). In particular, unhealthy food consumption is a behavioral problem as it depends on what consumers buy or choose. The term “health” is defined by the World Health Organization (1948) as complete physical, mental, and social well-being, not mere absence of disease. Following this logic, healthy foods are individual foods that promote such well-being, while healthy diets refer to the act of purchasing or consuming several foods that are also healthy. More information about whether a product is healthy does not necessarily increase healthy food choices, and providing the correct type of information, in the right amount, at the right time, to the right individuals, may solve this behavioral problem. Healthy food labels can be defined as the use of simplified information, symbols, or logos regarding the healthy aspects of food products. The effects of front-of-package food labeling, a specific type of healthy food labeling, have been extensively investigated regarding consumer behavior. Such labels indicate how healthy the overall product is, how healthy the specific nutritional content is, or a combination of both (World Health Organization, 2019). This was chosen because such front-of-package labeling itself transforms nutritional data into information for consumers, and such labeling may also undergo digitalization.

Figure 1

The Scope of the Thesis



Note. The scope of this thesis ranges from broad to narrow conceptualizations from top to bottom.

Digitalized healthy food labels can be classified in terms of digitalization and further into static, interactive, and technology-enabled labels. Static labels are healthy food labels presented in a digital format similar to physical labels, and interactive labels may provide more information about the labeling system or why the product is healthy. Technology-enabled labels may provide consumers with personalized, dynamic, and real-time information regarding why the products are healthy. Such symbols or logos may change appearance depending on different consumer segments and what consumers do when interacting with the device or the store, and they can be continuously updated if a novel labeling requirement occurs. For instance, a consumer may visit their favorite online grocery store, add the products to their virtual basket, and see a technology-enabled label that signals how healthy the overall basket is based on established food labeling systems. Similarly, they may present other consumers who rate certain products as healthy, whether they meet the consumer's individual nutrient-specific needs for that purchase situation or promote healthy products that are specific to the climate that the consumer is currently in. Furthermore, online grocery stores may be more innovative in such labeling systems. They could, for example, give the consumers the option to "build their own label" by presenting a list of product requirements that the user wants and placing labels on such products. Another example of innovative technology-enabled labels may be product labeling based on the diet of the consumer rather than individual products. For example, consumers may provide their activity levels, and labels can then be placed on different products, depending on what they bought the previous week. This may ensure their overall diet is healthy rather than focusing on the purchase of individually healthy products.

This dissemination also falls under the broader research related to digitalization and consumer behavior analysis. Digitalization is the use of digital technologies that provide new information or value beyond merely transforming analogue information into digital format (Mergel et al., 2019; Parviainen et al., 2017). It may benefit companies in generating profits and enable them to be adaptive in the market by, for instance, reducing manual steps, offering new products and services, and adapting to changing roles and value chains (Parviainen et al., 2017). Consumer behavior analysis is an interdisciplinary research field that studies consumer behavior using knowledge based on behavior analysis, behavioral economics, and marketing science (Foxall, 2003). This approach has the benefit of investigating how environmental or situational variables impact consumer behavior, and such variables can be changed directly rather than changing attitudes, intentions, cognition, thoughts, and beliefs in order to change behavior (Foxall, 2005). Within consumer behavior analysis, the operant systems perspective states that an entity’s behavior is impacted by the consequences that it produces, as well as its antecedent events. This applies to the behavior of consumers and companies. Based on prior research within impulsivity research, several studies suggest that self-monitoring, pre-commitment, and social factors may impact impulsivity (Duckworth et al., 2018), and these could be integrated with digital technologies in online grocery stores. Self-monitoring refers to the recording and presentation of one’s own previous behavior to promote behavioral change. Pre-commitment is the voluntary act of changing future consequences to set the occasion for behavioral change. Social comparison refers to information that signals how healthy current foods are compared to those of other consumers, and this could influence consumer preference. Furthermore, companies' behaviors are shaped by consumers through their reciprocal interaction (Foxall, 2020). Lastly, prior research also suggests that different actors have different definitions of what counts as "healthy" products, and that this confusion could impact consumer behavior (Mayer et al., 1993; Spiteri Cornish & Moraes, 2015). Building on this, these understandings may differ when public policy, retailers, and consumers making their purchases define what products count as healthy. Digital technologies may present and apply information based on these phenomena, and their impact on consumer behavior may be investigated. Hence, digitalized healthy food labels could present information beyond traditional healthy food labeling, and some could be used to address the problems mentioned.

1.4 The Main and Sub-Research Questions

The overall research question of this thesis is: "How do digitalized healthy food labels impact consumer behavior?"

The sub-research questions are as follows:

1. How do physical and digitalized static, digitalized interactive, and digitalized technology-enabled front-of-package food labels impact purchase, consumption, hypothetical choice, and self-reports regarding healthy foods?
2. What is the relative impact of (a) self-monitoring-based, (b) pre-commitment-based, and (c) social comparison-based technology-enabled healthy food labels on choice behavior in hypothetical grocery shopping settings, and how do they differ for impulsive and non-impulsive consumers?

3. Conceptually, how do technology-enabled healthy food labels emerge in the interaction between firms and consumers?
4. What is the relative impact of technology-enabled healthy food labels when they are defined by public policy, retailers, and consumers making the decision on healthy food consumer behavior?

The justification for investigating these research questions is as follows. Regarding the overall research question, the justification from a practical perspective is that unhealthy food consumption remains a significant problem for society, companies, and consumers. Furthermore, digitalization processes are becoming more apparent across many domains in people’s lives. Hence, more research is needed on this topic, and this research question is thus investigated. From an academic point of view, the overall research question is broad. Few conceptualizations exist, and it may be conceptualized in several ways. However, several research disciplines have already investigated elements related to how digitalized healthy food labeling impacts consumer behavior. This includes the literature on information systems, behavioral sciences, front-of-package food labels, digitalization, and consumer behavior analysis. Hence, synthesizing these was undertaken in order to shed light on how digitalized healthy food labels impact consumer behavior.

Concerning the first sub-research question, several studies on healthy food labeling use established terms and classifications, which may impact a broad range of consumer behaviors, and there exist several ways of presenting them using digital technologies. Hence, using prior literature, established terms, and investigating how digitalized labels allow for novel information and how it impacts a wide range of consumer behavior informs the overall research question.

With regard to the second, there exists much literature on unhealthy food choice viewed as an impulsivity problem with several proposed interventions to reduce impulsivity. Among these are strategies related to self-monitoring, precommitment, and social factors. Additionally, some vulnerable consumers, such as impulsive consumers, are prone to several risks, which include unhealthy food consumption. Hence, investigating which of these strategies, when presented as technology-enabled labels, impact choice behavior, and how these choices differ between impulsive and non-impulsive consumers, informs an important aspect of the overall research question.

Regarding the third sub-research question, there exist several ways to present technology-enabled healthy food labels, and this may influence how they impact consumer behavior. It is therefore of importance to analyze what type of technology-enabled labels are created, and one actor that could participate in this is online grocery stores. Hence, it is important to analyze how the creation of these labels occurs from the perspective of companies and how they impact consumers' behavior, and this important aspect informs the overall research question.

In relation to the fourth research question, several justifications are worth mentioning. First, healthy food labeling, the use of simplified symbols or logos to inform how healthy a food product is, depends on how it is explained to the consumers and the source of the information explaining the labeling system. Second, some literature has stated that there is a "health confusion" in that several actors have different definitions of what counts as healthy foods, and that this confuses consumers. One way is to use digital technologies to allow consumers to create their own labeling systems. Hence, the relative impact of technology-enabled labels defined by public policy, retailers, and consumers making the decision informs the overall research question in this important aspect.

1.5 The Contribution of this Thesis

This thesis's overall contribution is the investigation of digitalized healthy food labeling and its impact on consumer behavior. Specifically, it proposes and investigates a classification for different degrees of digitalized healthy food labels, how impulsive consumer segments respond to different technology-enabled healthy food labels, how companies and consumers' interactions are changed when companies implement digitalized healthy food labels, and how technology-enabled labels may allow consumers themselves to define what is healthy.

This thesis also contributes to the field of information systems research and behavioral sciences. In particular, it highlights novel combinations of conceptual frameworks, methods, framings, phenomena, and compositions (Leidner, 2020) related to how digitalized healthy food labels impact consumer behavior. First, this thesis contributes to mature, new, and original conceptual frameworks by using established classifications found in the front-of-package food labeling literature, examines how technologies can present novel labeling systems, and how they impact consumer behavior. That is, conceptualizations from information systems that describe digitalized healthy food labels, such as information technology, the traditional information technology-business alignment view, digital technologies, processes related to digitization, digitalization, digital transformation, and digital innovation, are used. Furthermore, conceptual frameworks from behavioral sciences, in particular consumer behavior analysis, such as the bilateral contingency model, the three-term contingency, the behavioral perspective model, impulsivity, and rule-governed behavior, are used to understand consumer behavior. These result in an original conceptual framework, which is proposed as future research for this thesis. Second, the methods in this thesis have varying degrees of rigor and innovation. In particular, conceptual analyses, systematic reviews, and conjoint experiments were used to investigate the phenomenon of this thesis. Third, the framing contain elements of superficial and deep framings in that the individual papers build on prior research and investigate narrow relations, although the thesis as a whole integrates multiple domains. For instance, different streams of the problem of unhealthy food consumption related to society, companies, and consumers are considered, and previous strategies such as hard and soft approaches to solve these problems are used. Fourth, the phenomenon of this thesis is the topic of how digitalized healthy food labels impact consumer behavior. It builds on a mature phenomenon by investigating how data is transformed into information to solve practical problems, a relatively mature phenomenon of healthy food labeling, although not typically investigated by information systems researchers, and on the emerging phenomenon of digitalized healthy food labels. Lastly, the composition of this thesis attempts to use colloquial, academic, and elegant writing. It does so by balancing the writing style for the general audience, academic audience within information systems and behavioral science researchers, and attempts to integrate this elegantly. The reader of this thesis will be the judge of the latter. These points, in combination with the specific literature, will be elaborated at the end of this introductory chapter.

The specific contributions for each paper are as follows:

Study 1: The effects of digitalized static, interactive, and technology-enabled front-of-package food labels had the same, lower, and higher effects on healthy food-related behaviors than physical labels, respectively. Furthermore, this study identified fewer articles on interactive and technology-enabled labels compared to static labels. The implications of these findings are that there is a research gap regarding the effects of interactive and technology-enabled labels on healthy food-related behavior, and the results of this study indicate that the latter may be effective in increasing healthy food-related behavior.

Study 2: The impact of self-monitoring, pre-commitment, and social comparison technology-enabled healthy food labels had the most to least impact on choice behavior in that order. Furthermore, minor differences were observed as self-monitoring labels had more impact on impulsive vs. non-impulsive participants, pre-commitment labels had more impact on impulsive vs. non-impulsive participants, and social comparison labels had more impact on non-impulsive than impulsive participants. These findings imply that the self-monitoring labels had a greater impact on food choice than financial incentives for selecting healthy food products provided by the precommitment labels.

Study 3: Technology-enabled healthy food labels allow for new bilateral contingencies between firms and consumers. Two technology-enabled labels are used as examples. One label may fulfill consumers' needs by clarifying what products they consider healthy, and another may fulfill needs related to food variety. In the marketing research section, the previous research, methods, and parameters of these two labels are discussed. In the marketing intelligence section, suggestions are provided to create a marketing intelligence system regarding these labels. In the marketing mix management, product, promotion, price, and place were analyzed. Healthy food products may be defined by their structure or function. These labels are a form of promotion that occurs as a result of rule-governed behavior. Price as a variable is analyzed by firms' and consumers' perspectives, and pricing methods regarding these labels are provided. Placement of these labels can occur at the overall basket level or the individual product level.

Study 4: The impact of technology-enabled labels based on definitions by the individual consumers making the decision, public policy measures, and retailers had the most to least impact on verbal reports of likelihood to purchase in that order. Furthermore, the findings show a difference between products and categories of what public policy and consumers define as healthy food products. Most participants indicated that they would react positively if they saw such labels in a real online grocery store.

The remaining part of this introduction chapter will introduce the following topics in order to provide the reader with the necessary knowledge to evaluate how the studies in this thesis bring forth the overall research question, the sub-research questions, and contributions. First, it will introduce the background regarding the problem of unhealthy food choices, the previously attempted strategies, the problem from a behavioral sciences perspective, and the problem from an information systems perspective. Second, it will introduce the conceptual framework of this thesis, consisting of its stance on the philosophy of science, relevant research on digitalized healthy food labels, and the operant systems perspective. Third, it will present the methods used and reflections on the studies in this thesis. Fourth, it will present the general interpretation of the findings, their implications for societal and academic issues, and ethical considerations. Finally, future research regarding a broader understanding of how companies' digitalization processes are shaped by consumers will be presented.

2 BACKGROUND

2.1 The Problem of Unhealthy Food Consumption

Unhealthy food choice is a problem that affects society as a whole in that more people are obese than before, and obesity (a) is is associated with non-communicable diseases, (b) may impacts mental health, (c) is a large economic burden, and (d) particularly impact low- and middle-income countries. For instance, the two primary causes of obesity are unhealthy food consumption and a sedentary lifestyle (World Health Organization, 2024). The same source points out that adult obesity has more than doubled since 1990, and one in eight people will be obese in 2022 worldwide. Being obese is associated with a higher risk of noncommunicable diseases, and it has been estimated that 5 million people died from diseases related to obesity in 2019. These diseases include diabetes, cancers, neurological and digestive disorders, and cardiovascular and chronic respiratory diseases. In overweight children and adolescents, obesity in terms of psychosocial consequences may impact academic performance, quality of life, and incur stigma and discrimination. It has been estimated that the economic burden of obesity will reach 3 to 18 trillion US dollars by 2030 and 2060 if nothing is done. Low- and middle-income countries are particularly affected by this as they face the double burden of malnutrition, whereby individuals are consuming excess caloric-dense foods, which are also poor in micronutrients.

These problems are now affecting companies, as they are currently experiencing more pressure from organizations and governments to solve this issue; it may lead to stricter regulations on what they can offer to consumers and damage their reputation. These issues may result in a loss of profit. For example, the World Health Organization (2020) has suggested reducing incentives for the food industry to continue the production of unhealthy food, and several countries have followed along (Popkin et al., 2021). Chile has implemented restrictions on the marketing of food products, and Brazil has banned unhealthy foods in schools. Together with other countries such as Mexico, Peru, Israel, and Uruguay, they have implemented warning labels on unhealthy food products. The World Bank Group (2020) states that more than 40 countries have taxes on sugar-sweetened beverages, and some research indicates that brands that are considered unhealthy are perceived as less healthy, more caloric, and cost less than food products with no brand information (Masterson et al., 2020). In the same study, participants perceived healthy food to have higher prices than unhealthy foods. Moreover, several studies show that consumers are willing to pay a higher price for healthier foods than unhealthy food products (Alsubhi et al., 2023). Several established online grocery companies, such as Tesco (Quinn, 2023; Tesco, 2012), Sainsbury's (n.d., 2021; Sainsbury's, 2021), and Walmart (n.d.), are now looking at how to promote healthier products, with or without the use of digital technologies. The implication of such research is that companies may face decreased profits as a result of having a poor reputation, that healthy food products are perceived to cost more, and that consumers are willing to pay more for healthy than unhealthy food products.

These problems also negatively affect consumers, as most state verbally that they want to eat healthier and that their needs and wants are not being met. A survey by McKinsey & Company (Grimmelt, 2022) suggests that 70%

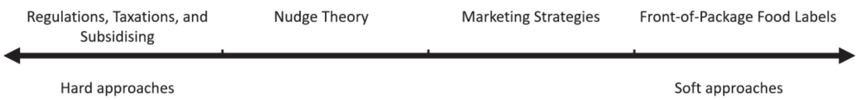
of participants stated that they want to be healthier, and 50% stated that healthy eating is a top priority, including reducing consumption of processed foods and sugar. Another survey by Deloitte (Edsall et al., 2022) suggests that, in spite of the recent inflation in the United States, consumers still state that they consider health and wellness when purchasing fresh food products. In the same report, 55% of consumers stated that they are willing to pay a premium for healthy foods, 48% stated that they are willing to share dietary preferences with grocers to personalize healthy food recommendations, and 48% are willing to use digital shopping websites or apps for such information. Similar results have also been found by NielsenIQ (2021), as roughly half of consumers stated that aspirational needs, in terms of achieving specific health goals, is a top priority, that this has become more important in the last two years, and that they are interested in products that can be customized to meet their specific health needs. In addition, three out of four consumers stated that they feel that product labels need to be more specific and transparent in order to help them make healthier choices. Similarly, roughly half of the participants said that they now care more about their health, and they spend more on healthier food products than before the COVID-19 pandemic (Kamel et al., 2021). LEK (Steingoltz, 2018) reports that consumers said they try to eat healthy most of the time and that three out of four said that they try to commit to eating in accordance with health, wellness, ethical, and environmental concerns. Based on these considerations, companies could improve in meeting consumers' needs and wants.

2.2 Previous Strategies

Several previous studies have investigated different strategies for these problems, ranging from hard approaches, which involve strict market regulations, to soft approaches, which involve education or companies themselves making efforts to address these challenges (Vecchio & Cavallo, 2019). Building on this, such approaches may include regulations, taxation, subsidies, nudging, marketing strategies, and front-of-package food labeling of certain food products. These strategies differ in their effect, practicalities, and ethical aspects in increasing healthy food choices.

Figure 2

Previous Strategies to Unhealthy Food Consumption



Regarding regulations, the banning of advertising unhealthy food and beverages is happening at public transportation networks in cities such as London and Amsterdam, and the Australian Capital Territory has done so public transportation networks, while premises at the Ministry of Health in Brazil, and on broader national levels such as Chile, Latvia, Ireland, and Finland (Chung et al., 2022) the same can be seen. The same study suggests that other studies have demonstrated a decline in purchases of sugar-sweetened beverages after Chile implemented its advertising law, school food policies, and warning labels. Regarding taxation and subsidies, some research indicates that taxes on unhealthy food and beverages show reductions in purchases of such products (Sacks et al., 2021). The practical implications are that some studies indicate a potential substitution of non-taxed unhealthy foods, which points to the challenge of defining what counts as healthy products. Furthermore, some research also indicates that price reductions in fruits and vegetables could lead to significant changes in consumption and purchases in an impactful way to produce health benefits (Huangfu et al., 2024). In terms of general practicalities of regulations and taxation, general barriers to these implementations include the question of what classifies as unhealthy foods, lack of political will, impracticalities concerning monitoring and enforcement, and public support. In relation to the ethical consideration of these approaches, they impose restrictions on consumer freedom in the sense that their choices are restricted.

Nudge theory can be defined as the study of nudges, and several articles exist on the subject of increasing healthy food choices. Nudges, as defined by Thaler and Sunstein (2009, p. 6), are “aspects of the choice architecture that alters people’s behavior in a predictable way without forbidding any options or significantly changing their economic incentives.” Several nudges have been proposed and studied in the context of increasing healthy food choices. For instance, some have investigated how accessibility, presentation of individual food items, use of messages and pictures, sensory stimuli, cognitive loading, and technology-supported information may help people live healthier lives (Ledderer et al., 2020). Others have investigated how descriptive and evaluative food labels, visibility, hedonic, convenience, size enhancements, and direct encouragement may impact healthy and unhealthy eating (Cadario & Chandon, 2020). Furthermore, some have investigated how altering properties, placement, or combining both of these factors influences healthy food choices (Tørris & Mobekk, 2019). Moreover, product placement, default options, priming, environmental cues, portion size, and food bundling have also been investigated in relation to promoting healthy food products (Vecchio & Cavallo, 2019). However, some authors (Vecchio & Cavallo, 2019) have suggested that although the majority of studies in their review found a positive effect, the practicalities are that the effects of nudge studies are often short-term, relatively small, and their use of non-representative samples may limit the external validity of these findings. The ethical implications of nudges are that they could be used unethically by not informing participants that such nudges take place, and one way to address this issue is by increasing the transparency of nudges or providing nudges that the participants can self-impose (Michels et al., 2023). Nudges differ from regulations, taxation, and subsidies of foods in that they alter people’s behavior by changing choice architecture without restricting choice or significantly altering economic incentives.

Marketing strategies, such as the marketing mix, which describes a combination of products, promotion, price, and placement (Kotler & Keller, 2016), may also be used to increase healthy food choices. For instance, some research has analyzed studies that used these factors and analyzed them individually or in combination with purchase and consumer-related behavior, and the results show that promotion may be effective in increasing healthy food choices (Karpyn et al., 2020). Furthermore, some have investigated whether commercial viability, retailer and customer perceptions, and societal outcomes in relation to product, price, placement, promotion, and combined elements of these produce favorable, neutral, unfavorable, or mixed outcomes in relation to healthy food retail strategies (Blake et al., 2019). There exists some research that has investigated factors that affect owners’ and managers’ decisions to use strategies to encourage healthy food purchases in consumers, suggesting that individual factors such as employees, interpersonal relationships, the store environment, community factors, sectors, policies, and broader sociocultural norms and values may impact whether they would support initiatives to encourage healthy food choices in consumers (Houghtaling et al., 2019). The practicalities are that grocery stores are the locations where consumers purchase their food products, and factors presented in these situations are likely to have more impact than interventions presented elsewhere. Companies are also more likely to continue using such interventions if they result in further profit. However, promoting healthy products based on limited consumer knowledge may also pose negative unforeseen consequences (e.g., the health halo effect; see Ikonen et al., 2020; Roberto & Kawachi, 2014). Marketing strategies are strategies to identify and meet human and societal needs (Kotler & Keller, 2016), and the marketing mix differs from regulations, taxation, subsidies, and nudges in the following manner. First, the actors of these strategies also include private companies, not limited to governments and countries. Second, these strategies emphasize identifying and meeting human and societal needs, not necessarily changing people's behavior, although they could do so. Lastly, these strategies can alter people's behavior by restricting choice or changing the economic incentives, for instance, by changing product options or price.

Front-of-package food labels signal to the consumers how healthy food products are and may be classified into summary, nutrient-specific (Hersey et al., 2013; Ikonen et al., 2020; Temple, 2020), or combined labels. Summary labels signal how healthy the product is overall and may be presented as single- or graded summary labels. Single summary labels are binary in that their presence indicates whether the product is healthy or unhealthy, while graded summary labels provide an evaluation ranging from a low to a high degree of whether the product is healthy or not. Nutrient-specific labels present several nutrients on the same product and signal that the nutrients are considered healthy. Similarly, they can be single and graded labels where each nutrient is presented as binary or specifying its value in a minimum and maximum range of how healthy the product is. In addition, nutrient-specific labels may be percentage-based as they illustrate how the nutrients of a product relate to the recommended daily intake of some highlighted nutrients. Combined labels use elements of both summary and nutrient-specific labels. Current and historical examples of these labels exist (Kanter et al., 2018). Single summary labels include the Nordic Keyhole (Forbrukerrådet, n.d.) in Norway, Sweden, Denmark, and Iceland, and Choice's Program label in the Netherlands, Belgium, Poland, and the Czech Republic. Similarly, an example of graded summary labels is the Nutri-Score (Ministère des Solidarités et de la Santé, 2022) in France. More recently, other countries, including Belgium, Spain, Germany, the Netherlands, Luxembourg, and Switzerland, have implemented this label system (Egnell et al., 2020). Examples of single nutrient-specific labels are warning labels (Reyes et al., 2019) in Chile, Finland, and Israel, and the 25% reduced label in Thailand. Graded nutrient-specific labels include traffic light labeling (Food and Drink Federation, n.d.), found in the United Kingdom, South Korea, and Ecuador. Percentage-based labels include Guideline Daily Amounts (Food and Drink Federation, n.d.) in the United States, the United Kingdom, and other European countries (Hersey et al., 2013). Lastly, an example of combined labels involves the Health Star Rating System (Department of Health, 2021), which can be found in Australia and New Zealand. Several systematic reviews exist on the topic. Some have examined their impact on (a) attention, (b) understanding, (c) reported and observed use or likely to use, (d) purchase behavior, and (e) likelihood of, reported, and observed consumption of foods related to these labels (Hersey et al., 2013). Others have looked at similar variables but also investigated perceived healthiness, tastiness, attitude, identification of healthy products, and choice of products in the context of these labels (Ikonen et al., 2020). Moreover, reviews have investigated these labels in the context of dual-processing theory, analyzing contextual and personal variables, system 1 or system 2 processing features, and choice features (Sanjari et al., 2017) in relation only to purchase behavior (An et al., 2021). Front-of-package food labels differ from regulations, taxation, subsidies, nudges, and marketing strategies in the following way. First, some of these labels are regulated by governments. However, such labels could be developed and used by private companies. Such labels could co-occur with taxes and substitutes, but they do not always imply this. Furthermore, these can qualify as nudges if they alter people's behavior without restricting their choices or economic incentives. However, if a country has implemented taxes on products with high sugar content, then a sugar warning label would not be considered a nudge because it changes economic incentives. Lastly, these labels could be viewed as a promotion in the marketing mix. However, they do not describe the whole marketing mix.

2.3 From a Behavioral Sciences Perspective

Within behavioral sciences, several approaches exist to study behavior, conceptual frameworks on why people engage in healthy behaviors, and how front-of-package food labels impact healthy food behavior. Behavioral sciences refer to any discipline that studies variables that impact behavior (Cohen et al., 2013; Hallsworth, 2023). The specific disciplines are defined by what behaviors they study or where they look for explanations. These are often measured in a quantitative manner. For instance, aspects of political science, sociology, clinical psychology, economics, health science, education, business, consumer behavior, and even information systems study what people do. These may include how many presidential vetoes occur in a given period, the proportion of women in the workforce, the number of business startups in a given location, whether people follow medical regimes, academic achievement, employee turnover, the number of products purchased by consumers, or whether consumers choose self-serving checkouts over traditional checkouts to decrease labor costs.

There are several conceptual frameworks within behavioral sciences and consumer behavior related to what influences healthy behaviors. In behavioral sciences, the health belief model, social cognitive theory, and transtheoretical model have been used to investigate health behaviors (Glanz & Bishop, 2010). Furthermore, Liu et al. (2014) suggest that overeating may stem from our tendency to overemphasize immediate benefits compared to delayed benefits, situations that may elicit certain emotions, and default options of unhealthy food products, and they proposed that strategies to increase healthy behaviors could be precommitment to healthy food choices, managing unhealthy cues, and using healthy defaults (Liu et al., 2014). In addition, Roberto and Kawachi (2014) have built on similar ideas but also propose avoiding unintentional consequences, investigating simplicity, framing, and providing meaningful communication regarding how healthy the food products are to consumers. Conceptual frameworks related to front-of-package food labeling and its impact on consumer behavior involve nudge theory (An et al., 2021), dual-process theory (Sanjari et al., 2017), and other interdisciplinary models (Hersey et al., 2013; Roberto et al., 2021; Taillie et al., 2020). In consumer research, although other disciplines have contributed to the study of consumer behavior (Holbrook, 1987), the main theoretical perspective has been cognitive explanations rather than how environmental variables contingent on behavior impact consumer behavior (Foxall, 2010). Consumer behavior analysis is an interdisciplinary research field that combines behavior analysis, behavioral economics, and marketing science (Foxall, 2016). Its goal is to describe, predict, influence (Cooper et al., 2020), and interpret consumer behaviors (Foxall, 1998) by investigating environmental or situational variables. This approach has the following benefits. First, food environments impact what consumers choose (Lake & Townshend, 2006), and arranging environmental conditions such that people make better choices is essential for obesity prevention (Sigurdsson et al., 2017). Second, research on consumer behavior incorporating situational events has more predictive power than research lacking this (Foxall, 2005). Third, environmental events impacting consumer behavior can be rigorously evaluated in controlled or closed settings or investigated in open settings (Fagerstrøm & Sigurdsson, 2015; Wells, 2014). Studying how consumer behavior changes due to environmental variables is also of practical concern for actors who want to promote healthier products. For instance, it may be more practical to change environmental factors rather than change people’s thoughts, beliefs, and attitudes. Furthermore, with the recent development of different technologies, one may better investigate the relationship between environmental variables and how they impact consumer behavior. More specifically, technologies may transform data into information that arranges environmental variables in a way that is based on the individual consumer rather than data based on the group level.

2.4 From an Information Systems Perspective

Within information systems, several new technologies have been proposed in retail settings, and several studies on how they impact consumer behavior exist. Information systems are characterized by collecting, storing, processing, and analyzing data to disseminate information to solve specific problems for decision-makers, typically bringing value to an organization (Rainer & Prince, 2021; Stair & Reynolds, 2018). The process of digitalization, the use of a specific type of new technology, is occurring in many aspects of our lives, including food and retail environments. Digitalization refers to the use of digital technologies that bring value to an organization or a consumer beyond merely transforming information in a digital format (Mergel et al., 2019; Parviainen et al., 2017). Digitalization strategies such as implementing mobile devices, wearables, smart speakers, augmented reality, virtual reality, mixed reality, Internet of Things, chatbots, smart mirrors, payment technologies, hand-held scanners, price scanners, RFID, and blockchain technologies (Shankar et al., 2021) have been proposed. Similarly, barcode scanning, smart carts, in-store coupon dispensers, kiosks, mobile apps, self-scanning, QueVision, smart shelves, personalized promotions and prices, and scan and go have been implemented (Inman & Nikolova, 2017). Grocery stores can use several digitalization strategies, and several variables related to healthy food choices have been investigated. Digitalization occurs in external domains such as vendors and products, marketing, prices, availability, and personal domains regarding desirability, accessibility, affordability, and convenience (Granheim et al., 2022). External domains include brick-and-click retail, food labeling requirements in online settings, prices related to delivery fees, and the number of available products in online settings.

Examples of personal domains include self-tracking apps for weight management, consumers' transportation needs, the affect of consumers' perceptions of price on intentions and willingness to use food delivery services and online food retail, and meal plans to reduce effort related to cooking and preparing food. Likewise, online food labeling, food swapping, default options, enhancing product salience, and combinations of these can be used (Valenčič et al., 2022). Similarly, translating or making information available, providing social reference points, changing choice defaults, efforts, range of options, and option consequences have been investigated (Wyse et al., 2021). The marketing mix approach has also been investigated in online grocery stores (Khandpur et al., 2020). Prices may be changed through discounts, rewards, and time-limited deals. Promotion may be used by displaying advertisements, branded content sites, social media, user feedback, and point-of-purchase information. Placements such as cross-promotion, search results orders, and recommendations in the online grocery store may be presented. Product mixes using personalized storefronts based on consumers' revealed preferences may also be used. Front-of-package labels in relation to other interventions that could be integrated with digital technology (Schruff-Lim et al., 2023) have likewise been examined. These interventions include reference information, educational material, training to use labels, presentation orders, health risks, basket feedback, social norms, healthy eating prompts, food swaps, financial incentives, and the introduction of new foods. Others have investigated real-time price, updated expiry dates, customer experience index, personalized offers (Fagerstrøm, Eriksson, et al., 2020), consumers' rating of healthfulness (Fagerstrøm et al., 2022), and product rating (Sigurdsson et al., 2024) of healthy foods.

Several scholars have also suggested investigating interactive and technology-enabled aspects of digitalization. In addition, personalized, dynamic, and real-time aspects could be investigated. For instance, Verhoef et al. (2021) state that some digital firms use analytics to personalize offers and services and tailor new offerings with dynamic pricing. Shankar et al. (2021) suggest that technology companies' use of interactive features and provision of personalized digital coupons could increase sales and consumer loyalty. Similarly, Inman and Nikolova (2017) state that retailers could use technologies to provide personalized coupons or content, change prices dynamically, and make personalized offers in real-time. Likewise, Valenčič et al. (2022) state that online environments have the potential for the personalized display of products in accordance with consumers' dietary needs. Vial (2021) states that dynamic capabilities and ethics related to digital transformation should be investigated and that digital transformation is broader in scope than information-technology-enabled transformation. In addition, others have investigated how personalized offers, real-time prices, updated expiry dates, and aggregated national customer experience indexes impact the likelihood to buy fish by using smartphone apps and the tendency to interact with them (Fagerstrøm, Eriksson, et al., 2020).

2.5 Research Gap

To the best of my knowledge, these were the research gaps during the initial stage of this thesis. First, there was a lack of systematic reviews on digitalized front-of-package food labeling on healthy food-related behavior. Second, there was a lack of research on technology-enabled labels derived from knowledge related to variables that minimize behavioral impulsivity, how consumers react to these labels, and whether some are more effective for impulsive consumers. Third, there was a lack of investigation into the development of technology-enabled labels from companies through their interaction with their consumers from a consumer behavior analysis framework. Fourth, there was a lack of research on technology-enabled labels where each consumer could define what products they consider healthy, how this impacts consumer behavior, and how this differs from public policy and retailer based technology-enabled healthy food labeling. There are also several research gaps based on information systems and behavioral sciences on the topic. Regarding information systems, little attention has been given to digitalized healthy food labels despite many overlapping research topics. For instance, there is substantial conceptual research on digital technologies (Bharadwaj et al., 2013; Hund et al., 2021; Vial, 2021), emerging retail technologies (Granheim et al., 2022; Inman & Nikolova, 2017; Shankar et al., 2021), and proposed digital technologies related to healthy food (Granheim et al., 2022; Pitts et al., 2018). However, relatively little attention has been given to developing a classification system and empirically examining the relative impact of novel digitalized healthy food labeling systems on consumer behavior. Regarding behavioral sciences, several conceptualizations exist on how to increase healthy food choices (Glanz & Bishop, 2010; Liu et al., 2014; Roberto & Kawachi, 2014), but few have been applied through the use of digitalized healthy food labels. Additionally, there exist several conceptualizations or empirical investigations on how environmental factors impact consumer behavior related to healthy food, such as the three-term contingency (Rafacz, 2019), the behavioral perspective model (Sigurdsson et al., 2017), delay discounting (Appelhans et al., 2018), and rule-governed behavior (Eriksson et al., 2023). However, few have employed these through the use of digitalized healthy food labeling. Lastly, even less attention has been paid to synthesizing these research streams into one conceptual framework that combines these with empirical investigations of these relations.

3 CONCEPTUAL FRAMEWORK

The conceptual framework of this thesis is the operant systems perspective in the context of digitalized healthy food labels and consumer behavior. This section will describe the necessary concepts and their relations by first stating its stance on the philosophy of science. It will then follow conceptualizations related to information systems, digital technologies, and digitalization. Next, it will present conceptualizations related to digitalized healthy food labeling and consumer behavior. Lastly, the operant systems perspective will be described based on previous literature on consumer behavior analysis.

3.1 The Philosophy of Science

The philosophy of science consists of explicitly identifying assumptions in research. This section will introduce this thesis' stance on the philosophy of science by stating assumptions about ontology, epistemology, and axiology.

Traditionally, the philosophy of science (or research) can broadly be classified by describing ontology (what reality is), epistemology (methods of deriving valid knowledge), and axiology (the value of knowledge acquired) (Saunders, 2009). In the context of ontology, this thesis assumes monism and determinism. It assumes one reality or world exists, while other stances, such as dualism, assume two realities or worlds. The reasoning is based on the mind-body problem associated with dualism in psychology (Baum, 2017) and the general problem of how one world impacts another. It assumes that we all live in a physical reality that we share and that our unique perceptions, judgments, and actions are physical events that are not occurring in another dimension. Furthermore, this thesis assumes that any phenomenon exists due to prior phenomena, including human behavior. This assumption is based on the view that phenomena do not come into existence without prior phenomena causing the former to occur (Cooper et al., 2020). However, identifying these relations empirically is challenging, as most have a probabilistic chance of occurring. For instance, not identifying all relevant variables that cause changes to the variable of interest, the presence of measurement errors, and studying phenomena characterized by complexity make studying these relations difficult. Building on these ideas regarding individual behavior, one may say that individual behavior results from people's genetic makeup, what they have experienced in their lives, and the situational context of these behaviors (Baum, 2017). Social phenomena occur when individuals interact but adapt to each other, and a group's decision may be more than the sum of the individuals' decisions. Hence, these phenomena are characterized by high degrees of complexity and emergent properties (see Axelrod & Cohen, 2008, for these terms). However, this does not rule out monism and determinism.

In epistemology, this thesis assumes that true knowledge or statements can be understood based on pragmatism. Pragmatism in the context of the philosophy of truth emphasizes that knowledge may be assessed by how well it promotes effective action by developing a conceptual economic framework that allows us to describe phenomena and their relation to other phenomena (Baum, 2017; Cooper et al., 2020). Actions are a way to change experiences or environments in a favorable way (Goldkuhl, 2004).

Pragmatism implies an interest in actions analyzed contextually; knowledge is demonstrated through actions and their practical consequences (Goldkuhl, 2004). This may differ from other approaches, such as realism (or a mirror view of science). In realism, there is a difference between objective and subjective phenomena, and valid knowledge is where our subjective perception matches objective events. Objective phenomena are typically described as real phenomena that are only indirectly perceived by our senses, which are subjective experiences. For instance, if someone's subjective experience led to them saying, "Under that table, there is a black cat", that statement is true if a black cat is underneath that table. Suppose several independent observers investigate this critically and come to the same conclusion. In that case, it is more likely that a black cat is there, which indicates that the statement is true. An alternative to this is pragmatism. Pragmatism builds on the idea that statements are true when they can reliably change experience, nature, or other phenomena, regardless of whether our subjective experiences match the objective phenomena. For instance, consider the statement, "The light is green." From a realism perspective, this statement would be true if it matched a green light. In pragmatism, if this statement reliably causes a change in events, such as people's behavior, then it is true that it has that function. For instance, if such statements reliably make people drive on the road or continue using the same strategy when working, they do indeed have that function. In pragmatism, the ontological, epistemological, and axiological approaches or strategies to find valid knowledge stem from the research question (Saunders, 2009), and the best method is the one that can demonstrate reliable changes in what is being studied. Following a pragmatic empiricist approach (Hantula, 2005), several methods may be used to investigate how environmental variables change consumer behavior. Examples of these include using laboratory experiments, microworlds, and field experimentation (Fagerstrøm & Sigurdsson, 2015).

In the context of axiology, judgments regarding value are important in research. These include which questions one asks, who benefits from these research findings, and the impact of such research. First, not all research questions are worthwhile, and those worth asking can have practical implications for society or advance a research field. All researchers have some prior background or knowledge regarding certain topics and methods, which influences the outcome of the questions being asked. Having value-free research on a complex topic such as digital technologies and consumer behavior may be unrealistic due to limited resources and the many different research fields, conceptualizations, and methods. Second, some research is more focused on providing benefits at a societal level for companies or consumers, while others try to combine contributions for all these actors. Some research emphasizes depth more, while other studies emphasize breadth and how much they cover. Again, these considerations are value judgments.

These points regarding the philosophy of science may have impacted this thesis and the studies in the following way. First, it assumes that individual consumers react to novel products presented by digital technologies due to their genetics, prior experience with these, and other situational factors (Baum, 2017). Although the former was not directly investigated, it was assumed that consumers have individual differences in preferences, while prior experience and current environmental variables were directly analyzed. In addition, these phenomena can be studied in various ways, both quantitatively and conceptually. Furthermore, this thesis does not aim to find a truth according to the criteria of realism and rather emphasizes pragmatism. Different digitalized labels were evaluated to determine whether they could reliably lead to effective actions or conceptual frameworks using systematic review, conjoint experiments, and conceptual analyses. The systematic review aimed to develop a clear classification for these labels, to identify previous research and labeling systems, and to investigate how they impact consumer behavior. The choice-based conjoint experiment aimed to investigate whether some technology-enabled labels based on variables that decrease impulsivity are preferred by consumers and whether some of these are more preferred by impulsive consumers. The conceptual paper consisted of describing the process of how technology-enabled labels emerge when companies interact with their consumers and how to understand this with emphasis on environmental variables. The rating-based conjoint experiment consisted of an examination of how different sources that explain what products are healthy impact consumer behavior. It may be too early to evaluate whether these findings can reliably change the state of affairs, as more research is needed on the topic, and these results must be looked at in light of the methods used. For instance, conjoint experiments are based on evaluations of hypothetical purchase situations, and these may differ from real purchase situations. The results of the experiment show that some technology-enabled labels are preferred over others, and the conceptual paper sheds some light on how companies may develop these labels. In terms of value judgments, it is still too early to evaluate whether companies will implement these findings and whether they are of value to consumers and society at large.

3.2 Information Systems, Digital Technologies, and Digitalization

Technology may be defined broadly as any human activity or artifacts of such activities that reliably solve practical problems or aid in achieving a practical goal (Dusek, 2006; Skolnikoff, 1994) and, it sometimes also refers to using scientific knowledge in business, industry, and manufacturing (Cambridge Dictionary, n.d.). Information systems are a type of technology. Such systems are characterized by collecting, storing, processing, and analyzing data to disseminate information to solve specific problems for decision-makers, typically bringing value to an organization (Rainer & Prince, 2021; Stair & Reynolds, 2018). Typically, data is processed into information or knowledge by specifying the information technology used. These are their hardware, software, databases, networks, procedures, and people using them. Organizations have used several types of information systems based on information technologies. Examples of these are transaction processing systems, functional area information systems, enterprise resource planning systems, office automation systems, management information systems, decision support systems, expert systems, and electronic commerce systems. Previously, such systems were developed to meet the strategic models of the organization. Furthermore, the adoption of new technologies is essential to be studied and several theories have proposed variables that may impact technology adaptation. These include theories such as the Theory of Diffusion and Innovation, the Theory of Task-Technology Fit, the Theory of Reasonable Action, the Theory of Planned Behavior, the Technology Acceptance Model and its variants, and the Unified Theory of Acceptance and Use of Technology (Lai, 2017). These theories describe how technology adoption occurs by specifying different segments and that they may have different needs and wants; characteristics of tasks and technology characteristics and their impact on performance and utilization; relationships between attitudes and subjective norms and perceived behavioral control on intention and then behavior; perceived usefulness and ease of use on attitude and then usage; and other variables that may moderate these effects.

It is essential to investigate how people interact with technologies. Building on this, Zhang and colleagues (Zhang & Li, 2005; Zhang et al., 2009) have proposed that human-computer interaction overlaps with information systems. They study how humans interact with technologies or information within an important social context, such as businesses, organizations, and cultural contexts. Within information systems, they investigated (a) what human-computer interaction consists of, (b) its relationship to other fields, (c) how it is evolving, (d) patterns of publication in information systems research, and (e) identified major contributing scholars (Zhang et al., 2009). First, such research focuses on organization, work, and marketplace contexts; it focuses on information technology use and impact over development: topics on information technology development, such as user interface design, development, and evaluation co-occurred most with research on information technology use and impact. Furthermore, empirical methods such as surveys, lab experiments, and field studies were frequently used; individuals, organizations, both, and none were most to least frequently studied; and end-computing is more frequently studied than organizational/social computing. Second, conceptual development from other research fields such as information, computing, communication services, behavioral and cognitive sciences, commerce, management, tourism, and services was common. Additionally, information systems, psychology, business, and management were the most co-occurring research disciplines, and information technology development topics were primarily built from more focused research fields compared to information and technology use and impacts. Third, more recent research focuses on other contexts besides than organization and workplace, especially on marketplace contexts; more research investigates several topics per paper; topics are primarily based on cognitive beliefs and behaviors; there is increasing research undertaken by using conceptual papers, studying groups, end-user computing with emphasis on web technologies, and behavioral and cognitive sciences research. Fourth, more human-computer interaction is becoming more dominant in primary information systems journals, and such journals encourage multi-disciplinary work, but have slight differences in topics, methods, and focuses on research disciplines. Lastly, there has been an increase in researchers and institutions publishing in human-computer interaction within these journals.

Traditionally, information technologies were first developed and then later assessed to determine how they impact humans, although this strategy is now changing. That is, information technologies were developed to meet and satisfy organizational strategic models. An alternative to this so-called business-information technology alignment view (Bharadwaj et al., 2013; Rainer & Prince, 2021) is to examine how technologies can be used to provide new value, and, in addition, be used to shape organizational strategic models themselves. There is now new emerging research related to information systems, technologies, contexts, and conceptualizations that integrates these increases in research as mentioned. These are related to digital technologies, digitization, digitalization, digital transformation, and digital innovation, especially within the marketplace context, such as studying consumer behavior. New technologies, such as digital technologies, may be used or developed by retailers to give consumers or companies more value. Digital technology is a specific type of technology that "*combines information, computing, communication, and connectivity technologies that transform business strategies, processes, firm capabilities, products and services, and key interfirm relationships in extended business networks*" (Bharadwaj et al., 2013, p. 471). Digital technologies overlap with information technology but contribute a different emphasis. Digital technologies do not add emphasis on hardware, software, database, network, procedures, and people using them because there exist several third parties that deliver these services and provide these features. Hence, companies may rather focus on the functional aspects of information delivery rather than specifying their structural properties. That is, focusing on what the technology can deliver instead of what it consists of. Following this, digital technologies may impact the scope, scale, speed, and source of value more flexibly than specifying their traditional information technology components and infrastructure. For instance, by examining what data is transformed into information, the operations needed for such a computation, how information is exchanged from one actor to another through communication, and how data is collected, exchanged, or manipulated from one actor to another through connectivity, it allows companies, in some instances, to focus on the most important aspects within an information systems rather than the information technology infrastructures.

Digitization includes encoding analogue information into a digital format (Hund et al., 2021; Mergel et al., 2019; Parviainen et al., 2017; Verhoef et al., 2021; Warner & Wäger, 2019). Extending this, digitalization refers to using digital technologies to provide new value beyond merely transforming analogue information into a digital format (Mergel et al., 2019; Parviainen et al., 2017; Verhoef et al., 2021; Warner & Wäger, 2019). In the last step, digital transformation refers to the process that aims to improve an entity by making changes to its properties, usually its strategic models, through the use of digital technologies (Verhoef et al., 2021; Vial, 2021; Warner & Wäger, 2019). For instance, Vial (2021) suggests a seven-step digital transformation conceptualization, which can be extended to digitalization. This framework differs from information technology-enabled transformation in that the entity is broader, not only related to specific organizations, has implications for other entities (individuals, companies, and society) (Vial, 2021), and has greater potential to redefine the entity's value proposition rather than using technologies to support established value propositions (Wessel et al., 2021). Vial (2021) states that combinations of digital technologies could impact business models and account for external factors. Specifically, digital technologies (1) may fuel disruptions, (2) and trigger strategic responses from entities, (3) to use these digital technologies, (4) which could enable changes in value creation paths depending on (5) structural changes and (6) organizational barriers, and (7) which affects positive and negative impacts. Another conceptualization presented by Verhoef et al. (2021) suggests three steps. These include external drivers, phases, and strategic imperatives of digital transformation. In the public sector, Mergel et al. (2019) state that digital transformation can be understood in the context of its reasons for implementation, what is being transformed, the transformation process, and the results of digital transformation. Wessel et al. (2021) undertook two case studies, one of which emphasizes digital transformation and the other focused on information technology-enabled organizational transformation, and propose their point of contact and departure. For both, this involves technological changes, transformation agendas, transformation activities, their outcomes, and imposition and reconciliation. More specifically, the environmental and organizational context may create a need for technological change, driving an agenda involving evaluating organizational identity, where digital technologies either redefine or support their existing value proposition, leading to the emergence of either new or reinforced organizational identity. The change in value proposition will result in changes in work practice and reconciliation of action, which again changes how digital technologies impact the value proposition.

These may lead to digital innovation, resulting in new artifacts (products, services, or tools) with some economic value (Warner & Wäger, 2019). Following Hund et al. (2021, p. 2), digital innovation may be defined as "*the creation or adoption, and exploitation of an inherently unbounded, value-adding novelty (e.g., product, service, process, or business model) through incorporation of digital technology.*" They state that digital innovation leads to the blurring of boundaries and the convergence of entities such as companies. This leads to shifts in focus on digital infrastructure, platforms, and ecosystems. Specifically, these are information technology and organizational structures supporting digital technologies and innovation, extendable code within software-based systems enabling core functionalities and modules, and a system described by the collection of platforms and modules, respectively. This leads to entities such as companies making strategic decisions driven by digital contexts or formulating and executing organizational strategies by using digital resources to create value. Entities and companies may, again, based on these, create digital objects, technologies, and innovation depending on their digital capabilities, organizational forms for digital innovation, and digital identity and cultures. More specifically, they are the capabilities to identify and respond to changes and opportunities, proper organizational forms and structures, and shared norms and beliefs within an entity.

3.3 Digitalized Healthy Food Labels: Static, Interactive, and Technology-Enabled

Digital technologies drive digitalization by providing value to consumers and companies (Parviainen et al., 2017; Verhoef et al., 2021; Warner & Wäger, 2019). They may also be used to present digitalized healthy food labels. Hence, digitalization of healthy food labels is an instance of the use of digital technologies that changes products and services that have some value, which are beyond mere digitization. However, presenting digital technologies could require relatively anywhere from little to complex processing. For instance, displaying static healthy food labels as they are presented in physical stores is a type of digitalization because they may attract consumers and provide them and the company with value by, for instance, transforming nutritional data into labeling formats. Interactive labels are similar to static labels, but they may also be presented with interactive information, that is, the option to gain additional information about the labeling system or the food product. Lastly, technology-enabled labels could present personalized, dynamic, and real-time information to consumers through digital technologies. Specifically, the label's appearance may change depending on the type of consumer and what they do in the online grocery store, and such labels may change based on real-time information, depending on whether labeling systems are altered. Furthermore, these digitalized healthy food labels can potentially allow digital transformation for online grocery stores as they gain knowledge regarding consumer insights, which may shape their business models. Finally, these could also be used for digital innovation in understanding how consumers react to novel digitalized healthy food labeling.

Research exists on the effects of digitalized static and interactive labels on consumer behavior. Regarding digitalized static labels, researchers have, for instance, investigated heart symbols, types of products, and health claims on consumer preference (Miklavec et al., 2021), gain versus loss-framing labels on the choice of products they would like to buy (de Alcantara et al., 2020), medium to high levels of fat with and without color coding on the identification of unhealthy food products (Antúnez et al., 2015), and different labeling systems on identification of the healthiest option (Hagmann & Siegrist, 2020). Some of these studies indicate a positive impact on consumer behavior (Antúnez et al., 2015; de Alcantara et al., 2020; Hagmann & Siegrist, 2020), while others found no or little differences (Miklavec et al., 2021). Regarding digitalized interactive labels, Finkelstein et al. (2021) investigated the impact of a physical activity equivalent label, a healthy choice label, a combination of these two, and no label on the purchase of products. When presented with the first two conditions, hovering their cursor over the physical equivalent label led to consumers viewing a text explaining that the number refers to the minutes an average adult would need to jog, equivalent to the calories for that product. Similarly, Sacks et al. (2011) examined the impact of traffic-light food labeling on sales of food products in an online grocery store, where the consumers could click on a specific section to view more details on nutrition information and the labeling system. Fuchs et al. (2022) created digital food labels using a Chrome extension that read the nutritional information on consumers' weekly grocery shopping. They could receive information about the nutritional aspects of the products. Similarly, Finkelstein et al. (2019) compared the traffic lights and Nutri-Score labels to the no-label condition on orders from an online grocery store. In all conditions, consumers had access to nutritional information for each product. Similarly, some found a positive impact on consumer behavior (Finkelstein et al., 2019; Fuchs et al., 2022), while others found little differences (Finkelstein et al., 2021; Sacks et al., 2011).

Some relevant research exists related to technology-enabled healthy food labels on purchase and choice of products with labels, total calories selected, orders, and participants' estimations of calories for foods. The majority of these found a positive impact. For instance, Braga et al. (2023) studied the impact of graded summary labels on individual products and a tally that counted the total scores of selected products in the basket. Shin et al. (2022) investigated the impact of labels on individual products and on the basket level, sorting of products by nutritional quality, an explicit tax on unhealthy food products, and a healthier substitute offer on the choice of products in a hypothetical online grocery store. Furthermore, De Bauw et al. (2022) examined the impact of labels on an individual level, at the basket level, scores of such labels of other consumers that were similar to the participants, and product recommendations to improve the values of the basket label of healthy and environmentally friendly food products on food choice. In restaurant menus, VanEpps et al. (2021) conducted five experiments to investigate the impact of (a) arbitrary or assumed meaningful labels in the form of emojis, (b) arbitrary or assumed meaningful labels in the form of traffic lights, (c) continuous or categorical traffic lights, (d) continuous or categorical calories labels which were dynamic and dependent on the choices of meals by the participants, and (e) static caloric labels on total caloric content, number of items selected with the labels, and average calories per item. Moreover, Shin et al. (2020) investigated the effects of dynamic food labels with real-time feedback, in combination with sorting products by these labels, on the nutritional quality of purchases. Specifically, these labels were presented as Nutri-Score values, time required to burn off calories by jogging, calories, sugar, sodium, saturated and total fats per serving, and percentage daily recommended intake at individual and basket levels. Lastly, Gustafson and Zeballos (2019) examined the impact of static caloric labels on ingredients and automatically updated caloric information based on the whole product that consumers ordered and estimated the calories of a sandwich.

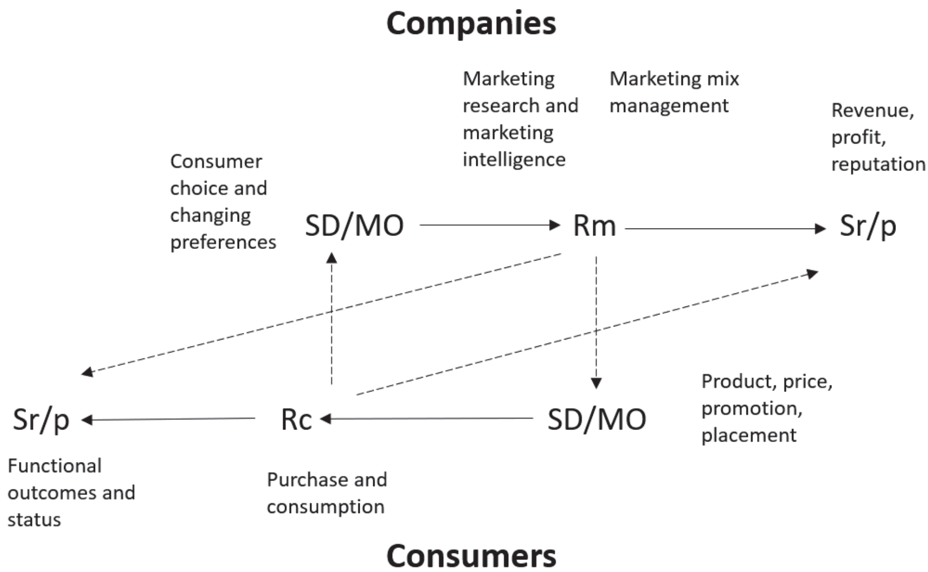
3.4 The Operant Systems Perspective

The operant systems perspective is a conceptual framework that specifies that an entity's behavior is impacted by its antecedent events and consequences (Foxall, 1999; Foxall, 2021). That is, it describes a three-term contingency, which specifies contingent relations between (a) the behavior, (b) the consequences, and (c) antecedent events. The presence of consequences and antecedent events depends on behavior, and these environmental and situational variables may impact behavior. This perspective may be used to analyze company behavior, consumer behavior, and their interaction. The latter is referred to as a bilateral contingency, as one entity's behavior acts as an antecedent event and consequence for another entity's behavior, and vice versa. That is, the reaction of one entity depends on the behavior of the other entity. In addition, the impact of technology-enabled labels on consumer behavior can be understood in this framework. This framework fits with digitalization literature because it emphasizes how environmental and situational variables impact consumer behavior, which is a core feature of digital technologies. Specifically, digital technologies can create value in the extended interfirm network by enabling new environments for each actor and connecting actors together. It can also be used to examine the interaction between how consumers shape companies, and vice versa, which is an essential feature of digital transformation. Lastly, digital innovation could be explored by enabling new environments.

Simply stated, companies' behavior is shaped by what consumers do, and consumers' behavior depends on what companies do. This may be analyzed by analyzing companies' and consumers' behaviors individually and then synthesizing their interaction (as shown in Figure 2). From the company's perspective, a company may perform behaviors such as marketing research, marketing intelligence, and marketing mix management activities. Some of these behaviors produce consequences such as changes to company revenue, profit, and reputation. The antecedent events, such as consumer choice and changing preferences, impact marketing research, intelligence, and marketing mix management. From the consumer's perspective, their purchases and consumption are impacted by the consequences these behaviors produce. For instance, owning and using products after purchase or gaining social attention when purchasing a highly valued good may change behavior. The antecedent events for consumer behavior could be specific products, promotions, prices, and placements. Some of these antecedent events signal that certain behaviors produce certain consequences, or they moderate the effectiveness of other consequences, antecedent events, or alter behaviors that have occurred under specific antecedent events or produced certain consequences. The company and consumers interact in the following way. A company's marketing mix management presents an offer to consumers. This offer is an antecedent event for the consumers in terms of purchasing or consuming the product. Consumer behaviors, choices, and changing preferences in terms of purchasing certain offers over others are the antecedent events for companies' behavior in terms of marketing research, intelligence, and marketing mix management.

Figure 3

The Bilateral Contingency Model



Note. Adapted from Foxall, G. R. (2021). The theory of the marketing firm: responding to the imperatives of consumer-orientation. Springer Nature.

Bilateral contingencies between companies and consumers can be analyzed in the context of developing technology-enabled labels. Companies may provide accurate and effective information about a product to change unhealthy food consumption, while consumers provide information about their purchasing habits. From the consumers' perspective, technology-enabled labels are a type of antecedent event that can be categorized under promotion and placement. Depending on the consumer's prior history with those antecedent events, they may impact purchase and consumption. From the company's perspective, marketing research, intelligence, and marketing mix management can be analyzed in relation to technology-enabled labels. Specifically, field experiments could determine whether they prefer labels based on their own nutritional needs at the basket or product level. Marketing intelligence systems could process what type of nutrients are more in demand in certain locations than others through these labels, leading to more insights into consumer decision-making. Marketing mix management may be based on introducing new technology-enabled labels.

The remaining part of this thesis introduces previous research and terminology on the operant systems framework to help the reader understand this conceptualization and the studies included. First, it will introduce previous research on this framework, which analyzes behavior at the individual and group levels, followed by research on companies and their interaction with consumers.

3.4.1 Individual-Level Consumer Behavior

At the individual level, the three-term contingency describes the relationship between antecedent events, behavior, and consequences (Catania, 2013; Pierce & Cheney, 2017; Skinner, 1953) in that temporal order, and it is used to analyze voluntary behavior (Skinner, 1976). Consumer behavior may be measured in several ways, consequences can be classified as reinforcers and punishers, and antecedent events can be classified as discriminative stimuli and motivating operations[1]. Consumer behavior, as with any behavior, may be measured by what it produces, that is, its functional definitions (Johnston et al., 2010). For example, functional definitions include money spent in a store, the number of vegetables bought, time spent on an app, the proportion of products disposed of at one recycling station over others, a consumer verbally replies to questions regarding products, and selecting one option over others (i.e., preference relations). Similarly, consumption of food, purchase of products, choice of products, and verbal reports about one's own behavior can also act as functional definitions. Consequences, such as reinforcers and punishers, are events defined by how they impact behavior. Reinforcers are consequences that increase behavior, and punishers are consequences that decrease behavior. For instance, purchasing behavior may increase if it produces access to fresh products, while gaining access to tasteless products may decrease purchasing behavior. Reinforcement refers to the procedure and process of delivering reinforcers, and where behavior increases due to the behavior-reinforcer contingency. At the individual level, consequences that reinforce one consumer's behavior may not reinforce another consumer's behavior or even another behavior for the same individual. Reinforcement and punishment are experimentally identified when (a) behavior produces consequences, (b) consequences change behavior, and (c) this change occurs due to the behavior-consequence contingency (Catania, 1973), where empirical evaluations of these criteria avoid circularity. Antecedent events, such as discriminative stimuli, signal the availability of behavior-consequence relations, and such

[1] Both are antecedent events, but describe fundamentally different environmental stimuli. Others use the three-term contingency for only describing discriminative stimuli, behavior, and consequences.

stimuli may increase behavior (Baum, 2017; Dinsmoor, 1995a, 1995b). For instance, a discount sign may increase the probability of purchasing products due to reinforcing the consequence of reducing the amount of money spent. Motivating operations are events that alter the effectiveness of consequences and alter behavior that has previously produced similar consequences (Langthorne & McGill, 2009; Laraway et al., 2003; Laraway et al., 2014; Michael, 1982). Establishing operations increases consequence effectiveness and the previous behavior that produced them, while abolishing operations decreases these two. For instance, not having access to food for a period of time may increase the reinforcer effectiveness of food on behavior and increase behavior that has previously gained access to food, while having the opportunity to eat decrease the reinforcer effectiveness of food on behavior and behavior that has previously produced food (Tapper, 2005). In nonbehavioral terms, motivating operations determine how much a consumer wants something (Fagerstrøm et al., 2010). Sometimes, this is referred to as the four-term contingency that consists of motivating operations, discriminative stimuli, behavior, and consequences[2].

The three-term contingency has been used to investigate several aspects related to consumer behavior (Wells, 2014), including behaviors related to healthy food. Consequences such as free shipping in a simulated online shopping experiment as assumed reinforcers (Fagerstrøm et al., 2011) and dietary feedback (Normand & Osborne, 2010) as punishers have been investigated on consumer choice between different online shopping stores and calories purchased. Discriminative stimuli such as promotional

[2] Others describe this contingency as contextual stimuli, discriminative stimuli, behavior, and consequence relations. The former conditionally impacts the second stimulus by signaling, not by MOs.

labels of Fair Trade coffee drinks (Stratton & Werner, 2013) and images of dish detergents with their benefits (Sigurdsson et al., 2010) in relation to types of coffee purchased and relative brand choice have been investigated. Motivating operations in terms of up-sell offers (Fagerstrøm et al., 2021), online recommendations (Fagerstrøm & Ghinea, 2011), corporate social responsibility messaging (Fagerstrøm et al., 2015), and their impact on conversion rate and revenue, as well as verbal reports of likelihood to purchase have been studied. In regard to healthy behaviors, digital technologies could be used to process or present antecedents and consequences to promote healthy behaviors (Dallery et al., 2015). When it comes to behaviors related to healthy food, healthy eating may be analyzed in terms of several choice responses where selection, preparation, and consumption may also be impacted by their consequences, discriminative stimuli, and motivating operations, though changing response efforts, delay to reinforcement, and monetary cost may also play a role (Rafacz, 2019). In grocery stores, prominent discriminative stimuli such as product placement and advertisement and their impact on sales of healthy food products (Sigurdsson et al., 2014), as well as the impact of price, quantity, delivery time, ratings of other costumers, secure checkout, health benefits, and environmental impact of choice of hypothetical fish purchase in online grocery stores (Sigurdsson et al., 2017) have also been examined[3].

Three important extensions of the three-term contingency relevant to this thesis are research on rule-governed behavior, delay discounting, and behavioral variability. Rule-governed behavior is behavior that is influenced by rules (or instructions). Rules are antecedent verbal stimuli that are

[3] Parts of this paragraph are taken from the candidate's assignment from a PhD course.

contingency-specifying stimuli (Skinner, 1969) and have a function-altering effect (Blakely & Schlinger, 1987; Schlinger & Blakely, 1987). Verbal stimuli are stimuli other people give, such as oral, textual, or symbolic stimuli. Contingency-specifying stimuli are verbal stimuli that describe three-term contingencies to a listener. For instance, “Buy products with the healthy food label!” describes the parts of the three-term contingency, while “Buying products with healthy food labels gives you a discount!” describes the full contingency. Rules have a function-altering effect, meaning they change the functions of antecedent events and consequences. For instance, a healthy food label may not impact behavior until someone explains or gives instructions to consumers on what such labels do. Different types of rules exist, and they have different dimensions. For instance, Zettle and Hayes (1982) suggest that tracks, plays, and arguments exist. Tracks are rules that impact behavior due to correspondence between rules and existing environmental contingencies, plys are rules that impact behavior due to socially mediated reinforcers, while augmentals are rules that change the function of consequences. Following the previous example, consumers may follow the rule because such descriptions are correct, because of others, and not necessarily based on the content of the rule, and therefore, the consumer is now also sensitive to the discount as part of the consequence features of the product. The dimensions of rules may include explicitness, accuracy, complexity, source (Peláez & Moreno, 1998), and time (Pelaez, 2013). Explicit rules describe the full three-term contingency, accurate rules correspond with actual contingencies described, complex rules describe events in conditional terms, sources may be given by others or by the consumer themselves, and time describes how immediate the consequences are. In the context of consumer behavior and rule-governed behavior, empirical and conceptual articles exist (conceptual paper, Fagerstrøm et al., 2010). For instance, research on rule-governed behavior has been used to investigate corporate social responsibility statements (Fagerstrøm et al., 2015), variables impacting the likelihood of booking hotel rooms (Eriksson & Fagerstrøm, 2018), and up-sell offers in online business-to-business retail (Fagerstrøm et al., 2021). Few have, however, investigated this in the context of healthy food labeling. Hence, healthy food labels can be viewed as an antecedent event that acquires the function of discriminative stimuli when they signal the availability of behavior-consequence relations or of motivating operations when they alter the value of consequences or impact behavior that has produced specific consequences when instructions are presented. Furthermore, some empirical articles exist on the source of rules that are self-provided (Baumann et al., 2009; Harte et al., 2017; Rosenfarb et al., 1992). However, few have examined how consumer behavior is impacted by labeling healthy food products based on the individual consumers' own explanations of what is considered a healthy food product.

Delay discounting refers to where the subjective value of a good decreases as the delay to its recipient increases; it is usually studied by varying the delay or amount of two reward options and is often described by a hyperbolic function (Green & Myerson, 2004; Odum, 2011; Rachlin, 2000). In other words, this phenomenon is a way to study impulsive or self-controlled decision-making, whether immediate and smaller rewards or delayed and larger rewards impact an individual's behavior. Typically, this phenomenon is studied by presenting options of obtaining a smaller and immediate reward and a delayed and larger reward, observing what individuals prefer, changing either the delay or amount of reward for one of the options, and observing whether individuals change their preference for one option over another. For instance, an individual may prefer obtaining £200 to £100 when both reward options are given immediately. However, the same individual may prefer to obtain £100 immediately to £200 in five years. Similarly, one individual may prefer obtaining £200 after one week over £100 immediately, but prefers £100 immediately to £101 after one week. After varying these, one may approximate the point where individuals are indifferent to choosing one of these options, referred to as indifference points. When one plots these indifference points and the value of the delay, one typically sees that indifference points decrease as a function of delay, and this decrease can be described by the following formula: $V = A / (1 + kD)$. V refers to subjective value (or indifference point), A is the objective amount of the reward, D is the objective delay to receive the reward, and k is an empirically derived free parameter used to determine the steepness of the formula (Mazur, 1987). Individuals who are very sensitive to delay and whose behavior decreases greatly as a function of delay have higher k-values than those who do not. Delay discounting can sometimes be analyzed as rewards acting as reinforcers that are less impactful on behavior as delay increases, behavior under the control of rules that describe delayed rewards in three-term contingencies (see Malott, 1989 for discussion), or both. There is research on how delay discounting differs as a function of different commodities (Odum et al., 2020; Weatherly et al., 2010), cultural differences (Du et al., 2002), and its relationship to delivery fees (Hantula & Bryant, 2005), sales promotions (Coker et al., 2010), credit card use in students (Fagerstrøm & Hantula, 2013), choice of short-term and long-term work tasks (Fagerstrøm et al., 2016), and food choice (Appelhans et al., 2018; Appelhans et al., 2019). Furthermore, investigating whether some technology-enabled labels are more effective for impulsive consumers may be of large societal importance, as obesity may be predicted by impulsive behavior (Bickel et al., 2021). However, few articles have investigated novel digitalized food labeling systems using knowledge of delay discounting and how that impacts consumers' choices of food products.

Behavioral variability can be defined as behavior that has variations in features of responding and can be studied by assuming that it can be described, predicted, and explained with reference to other phenomena (Johnston et al., 2010). Some research has investigated whether the delivery of consequences contingent on behavioral variability may increase such behaviors (Neuringer, 2002; Page & Neuringer, 1985), although there exist debates regarding the exact mechanisms of this phenomenon (Holth, 2012; Nergaard & Holth, 2020). Even if the exact mechanisms are unclear, research suggests that several procedures can reliably increase behavioral variability (Nergaard & Holth, 2020). Several procedures exist for studying behavioral variability. For instance, consequences may be delivered when the current behavior differs based on previous responses using threshold, frequency-dependent, and Lag n schedules procedures (Nergaard & Holth, 2020). Threshold procedures involve reinforcing responses below a specific frequency threshold. Frequency-dependent procedures involve reinforcing the least emitted available response. Lag n schedules consist of reinforcing sequences of responses that differ from the n previous emitted response sequences. For instance, if the current purchase differs from the previous or the fourth previous purchases, then they would fulfill the requirements of Lag 1 and Lag 4 schedules, respectively. Empirical studies have shown that behavioral variability can be changed by its consequences in humans and other species (Reed, 2023) and also through the use of discriminative stimuli (Reed, 2023). Furthermore, a systematic review of the Lag n schedule procedures on behavioral variability in humans indicates that it can be a promising behavioral technology (Silbaugh et al., 2021). Hence, labeling systems that signal products are healthy and distinguish current products from previous healthy purchases may be one way to increase variety in food choices[4].

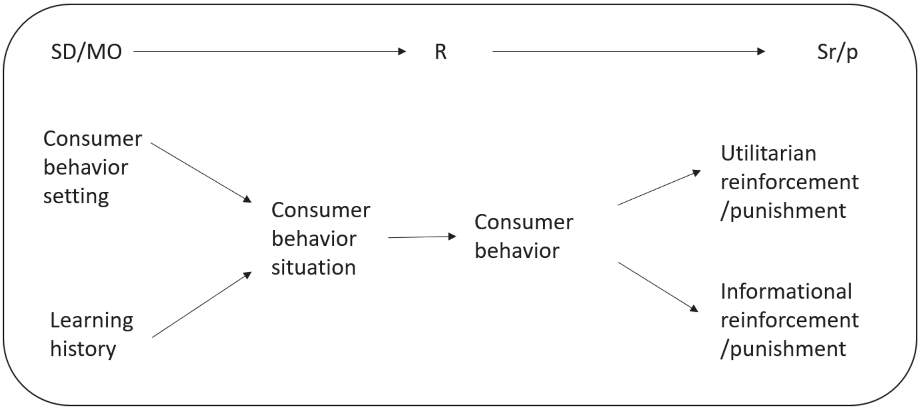
The behavioral perspective model is an extension of the three-term contingency that allows for the interpretation of naturally occurring events, introduces the concept of utilitarian and informational consequences and consumer behavior setting, and explicitly incorporates consumer situation and the learning history of consumers (Foxall, 2009; Foxall, 2020). Utilitarian consequences occur from the ownership and usage of products and services, while informational consequences occur due to social consequences provided by other individuals. For instance, purchasing a luxurious mobile phone may produce the reinforcing consequences of having a phone that performs well and consequences associated with conspicuous consumption, such as acknowledgment of wealth by others. Consumer behavior setting describes whether the consumers have a wide range of options (open settings) or a narrow range of options (closed settings). Learning history refers to past environmental events such that some goods and services act as reinforcers, punishers, discriminative stimuli, or motivating operations. Finally, consumer situation refers to the interaction between consumer behavior setting and learning history.

[4] Parts of this paragraph are taken from the candidate's assignment from a PhD course.

The behavioral perspective model has been used in the context of e-mail marketing (Sigurdsson et al., 2016), Wi-Fi on consumers' hotel bookings (Eriksson & Fagerstrøm, 2018), corporate social responsibility activities on purchasing workout clothes (Fagerstrøm et al., 2015), fashion products bought on Facebook (Menon & Sigurdsson, 2016), purchasing MP3 players from online retailers (Fagerstrøm & Ghinea, 2011), purchasing of fish products (Sigurdsson et al., 2017), and purchasing vegetables and fruits (Sigurdsson et al., 2011). For instance, Sigurdsson et al. (2016) investigated how the highlighting of discounts (utilitarian consequences) with and without celebrity endorsements (informational consequences) impacts openings, clicking on images, sales, and opt-outs on advertisements of bicycles for consumers who need and do not need bicycles (motivating operation). The results show that the most effective e-mail marketing strategy was utilitarian consequences with consumers who needed a bicycle, indicating the presence of establishing operations. Another example involves a study by Eriksson and Fagerstrøm (2018) that investigated the impact of Wi-Fi review, Wi-Fi price, hotel rating, brand, and price per night on the reported likelihood of hotel booking. These stimuli were interpreted as rules. They found that hotel rating, price per night, Wi-Fi review, Wi-Fi price, and the brand had the most to least impact on the likelihood of booking in that order. Similarly, Fagerstrøm et al. (2015) investigated price, brand, product wash, corporate social responsibility activity, and product quality on the verbal likelihood of purchasing workout clothes. These factors were interpreted as rules, and they had the most to least impact on the likelihood of purchasing workout clothes in that order. Additionally, support for the pink ribbon was preferred over ethical trading initiatives, and the latter was preferred over Green Warriors. In a similar fashion, Menon and Sigurdsson (2016) found that price, guarantee, shipping, pictures, order channel, size, and charity had the most to least impact on the verbal likelihood of purchasing fashion products through Facebook. These stimuli were discussed as signals of utilitarian and informational consequences, such as price being money spent, but also as an indication of the prestige of owning luxury products and charity as helping others. Likewise, Sigurdsson et al. (2017) found that product quality rating by customers, delivery time, secure checkout, environmental impact, price, quantity, and health benefits had the most to least impact on the choice of fish products in that order. These results were discussed in several acting three-term contingencies among several behaviors (e.g., the matching law; Baum, 1974; Herrnstein, 1970) in the context of utilitarian and informational consequences. Sigurdsson et al. (2014) found that placing healthier products in specific areas of a physical store increased the purchase of such products, and such placement can be viewed as a prominent discriminative stimulus.

Figure 4

The Three-Term Contingency (top) and the Behavioral Perspective Model (bottom)



Note. The former shows relations between discriminative stimuli (SD), motivating Operations (MO), behavior (responses, or R), reinforcement (Sr), and punishment (Sp). The latter additionally shows consumer behavior setting, learning history, consumer behavior situation, utilitarian and informational consequences. Adapted from Foxall, G. R. (2021). The theory of the marketing firm: responding to the imperatives of consumer-orientation. Springer Nature.

3.4.2 Group-Level Consumer Behavior

The three-term contingency has been extended to the group level by viewing groups as one behaving system (Foxall, 1999; Foxall et al., 2021) and examining how two systems may influence each other regarding bilateral contingencies (Foxall, 2020). The bilateral contingency model describes how the behavior of one system in terms of the three-term contingency interacts with another system with three-term contingency. For instance, a company's behavior may be influenced by antecedent events and consequences that the consumers provide contingent on the company's behavior, and consumers' behavior is influenced by the antecedent events and consequences that a company provides. A company may, in the presence of antecedent events such as consumer choice and changing preference, perform behaviors including conducting different market research, marketing intelligence, and management of marketing mix to achieve the consequences of increasing revenue and profit or building a good reputation. Similarly, a consumer base may be in the presence of antecedent events such as the presentation of products, price, promotion, and placement. The bilateral contingency model has been used in several theoretical and empirical applications. These include co-creation processes for dairy companies (Fagerstrøm, Bendheim, Sigurdsson, Pawar, et al., 2020) and idea sharing for LEGO (Fagerstrøm, Bendheim, Sigurdsson, Foxall, et al., 2020), marketing research and intelligence strategies to identify potential reinforcers for cosmetics (Haddara et al., 2020), companies that sell fish to consumers in Iceland (Alemu et al., 2020), social media campaigns in an aviation company and customer posting engagement (Sigurdsson et al., 2020), the relationship between consumers' efficiency (energy spent) and retailers' strategies to respond to these issues (Larsen et al., 2020), organizational strategies regarding environmental concern depending on consumer behavior settings and combinations of utilitarian and informational consequences (Foxall, 2018), and marketing and finance (Porto & Robert Foxall, 2019).

In the context of co-creation, Fagerstrøm, Bendheim, Sigurdsson, Pawar et al. (2020) examined how a dairy company's behavior and other consumers provide environmental variables that may impact consumers' likelihood to share ideas with the company regarding co-creation.

Specifically, their results show that money given by the company, the company's evaluation, and other consumers' evaluations of the ideas had the most to least impact on sharing ideas in that order. Within each factor, the following levels were preferred the most: 100 NOK per idea approved, the idea is awarded the best by the company, and sharing by other customers of the idea on social media platforms. Companies that adapt to these changing consumer preferences may acquire more profit, and other consumers may receive better products and services, influencing their liking and sharing of other consumers' ideas. Similar variables were investigated when consumers shared ideas with LEGO (Fagerstrøm, Bendheim, Sigurdsson, Foxall, et al., 2020). From the customers' perspective, the behavior of sharing ideas could be impacted by the company's verbal stimuli, followed by the approval of ideas by the company or other consumers. Verbal stimuli like antecedent events ("You design. We make it,"), or where consumers acquire points in terms of Lego Clutch Power as consequences of this, exemplify this relationship. From the company's perspective, its decision to implement an idea in the context of posts with more likes and other customers' approval may generate more profit. From other customers' perspectives, their likes and sharing in the context of customers' posts also generate these Lego Clutch Power consequences, as well as better available products.

Regarding marketing research and intelligence, Haddara and colleagues (2020) used data mining techniques on customer review data to identify potential reinforcing consequences of lipstick purchases. Specifically, they analyzed the most common words and correlations among them and in different consumer segments, such as age and skin tone. The six most common words were color, lipstick, like, look, lip, and nude. Their correlations indicate four major classes that may describe lipsticks with moisture, odor and taste, natural color, rich colors, and minor classes in specific segments such as original lip condition and original skin tone. Their interpretation is that these words may be used to identify products with reinforcing consequences for all consumers and different segments. In the context of companies that sell fish to consumers in Iceland, Alemu et al. (2020) conducted two studies, one on companies and one on consumers' behaviors related to their interaction. Managers in the company stated that they have several aspects related to online marketing, profitable operations, identifying customer choices and preferences, and conducting marketing management in reaction to these changing preferences. For instance, they have a social media presence, reduce transaction costs by outsourcing the creation of web platforms, identify that consumers want fresh and healthy fish and convenience, and run tests of sales before launching new stores. Most consumers said that they purchase fish because it tastes good, and buy fish online due to its convenience. They also found that price, preparation method, production method, order placement, and health claims of fish products impact the choice of fish products, and identified five different consumer segments based on this. Specifically, they categorized consumers as product-attribute-conscious consumers, those satisfied with physical stores, fresh fish-preferring consumers, those who prefer online stores, and price-sensitive consumers. Their results show that companies and consumers adapt to each other as they both focus on fresh and healthy aspects of products, and online stores may provide convenience in providing information related to these aspects in a simplified manner.

4 METHODOLOGY

This thesis employs systematic reviews, choice-based conjoint experiments, case studies, and rating-based conjoint experiments to analyze how digitalized healthy food labels change consumers' behavior. These methods were chosen for the following reasons. First, systematic reviews have the benefits of identifying prior literature on the topic, answering specific research questions, and allowing for transparency and replicability by other researchers. The justification for selecting this is that there exist several studies on healthy food labeling on a wide range of consumer behavior that use established labeling systems, and these were investigated in the context of digital technologies. Second, conjoint experiments allow for studying how products and services that are yet to be on the market impact consumer behavior, how these differ across consumer segments, and may inform managers through data-driven decision-making. Hence, they can be used to study product preference related to established and innovative features. They also require consumers to make trade-offs rather than rate individual items separately, adding realism by operationalizing attributes and levels, which are used for product development, pricing, competitive positioning, market segmentation, and informing managers through data-driven methods (Orme, 2020). In the context of the specific sub-research question, they allow empirical investigations of how technology-enabled healthy food labeling impacts consumer behavior based on environmental or situational factors and allow for comparison with consumer segments.

4.1 Systematic Reviews

Review papers (sometimes referred to as literature review papers) use previous literature to address some research question(s). One can categorize them into narrative or systematic reviews. Systematic reviews differ from narrative reviews in that they use explicit and systematic methods and syntheses of results to address a clearly formulated question. They are used to identify, extract, and synthesize knowledge based on papers included in the review. This thesis used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 (Page, McKenzie, Bossuyt, Boutron, Hoffmann, Mulrow, Shamseer, Tetzlaff, Akl, et al., 2021). The PRISMA 2020 papers consist of one original paper (Page, McKenzie, Bossuyt, Boutron, Hoffmann, Mulrow, Shamseer, Tetzlaff, Akl, et al., 2021), one explanation and elaboration paper (Page, Moher, et al., 2021), and one developmental paper (Page, McKenzie, Bossuyt, Boutron, Hoffmann, Mulrow, Shamseer, Tetzlaff, & Moher, 2021). The PRISMA 2020 consists of 27 items that a systematic review should include. These are identifying the paper as a systematic review, using the abstract checklist, providing a rationale for review, explicit research question(s), setting eligibility criteria, specifying information sources, a search strategy, a selection process, a data collection process, data items, study risk of bias assessment, effect measures, synthesis methods, reporting bias assessment, certainty assessment, a study selection, study characteristics, risk of bias in studies, results of individual studies, results of synthesis, reporting bias, certainty of evidence, a general discussion, registration and protocol, support, competing interests declaration, and the availability of data.

4.2 Rating-Based Conjoint Experiments

This thesis uses a rating-based conjoint experiment to evaluate the effects of different digitalized healthy food labeling systems on verbal estimations of the likelihood of purchasing hypothetical food baskets.

Conjoint experiments (sometimes called conjoint analyses) are a method for studying how participants' evaluations of hypothetical tasks change when the content of these tasks changes (Green & Srinivasan, 1978; Hair et al., 2014; Orme, 2020). They help study products that are yet to be on the market, as one can assess how different hypothetical product attributes change consumer behavior. This approach consists of creating experimental designs in which participants are asked to evaluate one or several alternatives and then conduct statistical analyses (usually regression analyses) to estimate the relationship between the participants' behavior and the studied product features. An experiment systematically measures how a dependent variable(s) relates to another independent variable(s), while experimental design refers to the plan for arranging the experiment. Quasi-experimental research designs involve manipulating the independent variable without randomizing the research units (Shadish et al., 2002), and conjoint experiments can thus be viewed as a type of quasi-experiment.

In rating-based conjoint experiments, one profile (concept, stimulus, or alternative) is presented at a time and jointly with several independent variables, and participants' evaluation of these is the dependent variable. For instance, the overall evaluation (sometimes called utility) for each profile could be collected from the following question: "On a scale from 1 (Definitely would not) to 7 (Definitely would), how likely are you to purchase this product?" The independent variables could consist of product features offered to the consumer, and they must be realistic and understandable. For instance, a study may investigate how strongly price, delivery time, and specific stores impact consumers' evaluations. In this case, the independent variables (attributes, factors, or features) are price, delivery time, and store name. Furthermore, each independent variable may have different levels (or values). For instance, levels for the price could be £50, £60, or £70; delivery time could be “In one hour,” “In six hours,” or “Next day;” and the name of the store could be “Sainsbury’s,” “Tesco,” or “Asda.”. Creating a profile with all possible combinations may be too much for participants to evaluate (e.g., in the example leading to 3 x 3 x 3 = 27 profiles). One strategy is to use an orthogonal design to reduce the number of profiles. Orthogonal experimental designs arrange different levels of independent variables that present a subset of all possible arrangements but do so in such a way that the levels do not correlate with one another, typically by using catalogues or algorithms. For instance, one can reduce the 27 profiles to nine profiles (Orme & Chrzan, 2017) and use the latter in the study. The experimental design of such a study may present all nine profiles to each participant and collect their evaluations. The order of such profiles may itself impact consumer behavior (i.e., order effects), and this could be corrected by presenting the profiles and the independent variables within a profile in random order (see Chrzan, 1994 for discussion).

The regression output and importance values are the most important statistical analysis outputs in rating-based conjoint experiments. Regression output involves presenting the estimates of the dependent variable as a function of the predictor variables used (sometimes called part-worth utilities), their standard errors, p-value, whether the predictor variables were treated as continuous or categorical variables, whether the model is was a linear or polynomial, specifying reference category by the use of dummy or effects coding, the f-statistic, and R^2 and adjusted R^2 of the overall model (see Field et al., 2012; Hair et al., 2014 for an overview). Usually, the ordinary least squares method is used to find the best-fitting model, where a model with the least sum of squared residuals is better than one with a larger sum of squared residuals. Relative importance scores are a way to compare the impact of each independent variable relative to others (Orme, 2020). This is usually calculated by taking the range of estimates of each independent variable separately and calculating the proportion of the range of one independent variable compared to the ranges of other independent variables. One may create an aggregated model based on all participants' responses or create separate models for each participant.

4.3 Choice-Based Conjoint Experiments

This thesis used a choice-based conjoint experiment to evaluate the effects of different digitalized healthy food labeling systems on the choice behavior of purchasing hypothetical food baskets. Choice-based conjoint experiments (sometimes referred to as the broader category of discrete choice experiments) build on a similar approach to rating-based conjoint analysis. Both involve designing an experimental design where the levels do not correlate with each other, presenting profiles, and investigating how consumers evaluate these. However, choice-based conjoint analysis differs in three main ways. First, several profiles are presented within one trial, and the participants are asked to select one in the context of a question. For instance, the question could be: "If these were your only alternatives, which would you like to buy?" Second, one of the profiles of the task can be a "None" option; that is, they would not select any of the other profiles. Third, the dependent variable is a binary (nominal or discrete) choice behavior instead of a continuous rating scale; that is, the profile was either selected or not. Similarly, regression analyses are used to investigate how each independent variable and its levels impacts choice behavior.

In choice-based conjoint experiments, one choice trial presents several profiles, where profiles consist of several independent variables jointly. Similarly to rating-based conjoint experiments, the independent variables and levels must be realistic and understandable in the context of the research problem. Several strategies exist to reduce all possible combinations of levels when creating profiles and to create an experimental design that ensures little correlation between the levels of each independent variable. Some designs, such as balanced overlap, which is the default option when using Sawtooth Software Lighthouse Studio, allow some correlation between the levels, which in turn allows for investigating interaction effects. In addition, order effects, such as the order of the choice trials, profiles within a choice trial, and attributes presented in a profile, can occur (Chrzan, 1994), and some of these designs minimize that.

The most important statistical analysis outputs in choice-based conjoint experiments are the logistic regression output, latent class analyses, hierarchical Bayes estimations, and relative importance values (Orme & Chrzan, 2017). The same binary data may be expressed in probability, odds, or the natural logarithm of odds. Probability in the context of choice data may be measured by counting how many times something was selected and dividing it by the number of times it was selected plus the number of times it was not selected. Odds may be measured by counting the number of times something was selected and dividing it by the number of times it was not selected. The natural logarithm of odds involves using the odds of something happening as the input in the logarithm with e as the base. Logistic regression output presents the estimate, standard errors, t-ratio, log-likelihood, and other measures. It differs from rating-based conjoint analysis in the following manners. First, the estimates represent the natural logarithm of odds of choice as a function of predictor variables. However, these may be transformed back to odds or probability by exponentiating these coefficients in base e for easier interpretation. Second, maximum likelihood is used to find the best-fitting model, and a model that has a higher log-likelihood with the predictor variables is better than a model with a lower log-likelihood. In choice-based conjoint experiments, the suggested weights of several predictor variables are summed for each profile in a trial, the log-likelihood for each choice trial is calculated given the observed choices, the sum of these represents the overall model log-likelihood, and the weights are adjusted to produce the highest overall model log-likelihood. Specifically, it can be described as follows.

$$U_i = B_j X_i + \varepsilon_i$$

$$P_i = \frac{e^{U_i}}{\sum_1^k e^{U_i} + \cdots + e^{U_k}}$$

$$P(A) = \frac{e^{U_a}}{e^{U_a} + e^{U_b} + e^{U_c}}$$

The first formula (Orme & Chrzan, 2017, p. 132) describes that U_i is the sum of the coefficients and presence of each level ($B_j X_i$) plus an error term ε_i for the profile i. The second formula (Orme & Chrzan, 2017, p. 133) states that the probability of choice of i, is when U_i, which is the sum of the coefficients and presence of levels for one profile, is used as the exponent with e as the base, is divided by the sum of the coefficients and presence of levels for one profile, is used as the exponent with e as the base, plus, the sum of all profiles up to k, individually. The third formula (Orme, 2020, p. 180) shows the same as the last in the case of a three-profile situation, the probability of choosing A when profiles B and C are present.

Similarly to rating-based conjoint experiments, the predictors may be assumed to be continuous (linearly or polynomially) or categorical (using dummy or effects coding), and estimates are thus interpreted based on the reference category. In latent class analyses, different consumer segments can be identified by constructing several logistic regression models, observing whether the choices fit in one model or another, and collectively finding a model with the highest log-likelihood. This approach is similar to factor analysis, although it assigns the probability of one case belonging to a segment, each associated with conditional regression output, describing the natural logarithmic odds for each predictor coefficient for that class. Hierarchical Bayes is an iterative method that first estimates a model based on all participant's behavior (i.e., the upper model), suggests weights at the individual participant level (i.e., the lower model), uses information from the overall model in the context of how individual participants models deviates from this, and based on algorithms is used to estimate individual participant weights for predictor variables. Similarly to rating-based conjoint experiments, these models can be used to find relative importance values calculated by finding the proportion of the range estimates of one predictor variable compared to the ranges of estimates from other predictor variables.

5 REFLECTIONS

The systematic review in this thesis was the initial starting point for investigating the effects of digitalized healthy food labeling on consumer behavior. Several considerations were taken before starting this paper. First, systematic reviews have the benefit of covering a large amount of literature and can lead to better identification of research gaps and investigation of the research question. Second, prior to conducting the systematic review, several review papers on the effects of front-of-package food labeling on consumer behavior were used as a foundation from which to identify the research gaps, formulate the research question, and explore previous reviews and research done on digitalized front-of-package food labeling. Third, the PRISMA framework was used because it increases the transparency of the review process by specifying the 27 items. However, several points are worth mentioning when conducting this systematic review. First, systematic reviews are often time- and resource-consuming and involve several collaborators. This systematic review took about one year, from reading other review articles within the front-of-package literature to developing a research question, creating the search strategy, data collection, synthesis, and writing the paper. Second, an ideal systematic review would also have inter-rater reliability on the risk of bias assessment and data collection. Due to restrictions on time and resources, this was only performed by one reviewer. Third, most of the data collection and processing was done manually, and automated tools could have been used to reduce human labor. Finally, this systematic review may have been narrow in scope, restricting itself to the front-of-package food labeling literature. There are established taxonomies (e.g., summary or nutrient-specific labels) in that literature, and these were selected in order to follow previous research standards. There are several points on how the systematic review informs the overall study. First, it informs prior research undertaken on digitalized front-of-package food labeling in terms of static, interactive, and technology-enabled labels and found decreasing publications on these labels in that order. Second, the types of independent variables that were investigated in prior published studies informed the overall study and made it possible to investigate other labeling systems that were explored in the remaining studies of this thesis. Lastly, it also informed that prior studies, one choice-based and one rating-based conjoint experiments, were investigated regarding the impact of the effects of digitalized static labels on consumer behavior. It informed the study that these methods are valid, but were used to study static labels and rather than technology-enabled labels.

The choice-based conjoint experiment was the second study in this thesis. Likewise, several considerations were taken before starting this experiment. First, the systematic review indicated little prior research on technology-enabled labels, and a natural step was to research that label form. Second, the broader term "healthy food labeling" was considered rather than front-of-package food labeling. Third, the research question was asked based on previous literature on consumer behavior analysis. The degree of delay in receiving a commodity impacts people differently. People who are very sensitive to delay, or impulsive in layman's terms, are more prone to a wide range of behavioral problems. Hence, identifying what technology-enabled labels are more effective for impulsive people is of high societal importance. This study was an online study and used participants from Prolific.co. Standard procedures for conducting experiments with humans were followed, such as providing informed consent forms, minimizing the collection of personal data, and sending an application for SIKT.no in line with their recommendations. Several points regarding the findings of this paper are worth mentioning. First, some order effects could have occurred because the order of the attributes was always the same, and the introduction of what the technology-enabled labels do was also introduced in the same order. Regarding the latter, randomizing the order of introducing the labels would also confound the results if different segments received different orders. This led to the decision that all participants be exposed to the same sequence to minimize the latter confounding, following the principle of “all else being equal.” Second, the results of this study may be culture-specific in that UK participants were investigated. These results could be different when using participants from countries where such participants are more price-sensitive. Furthermore, all participants were recruited from Prolific.co. Although the study collected participants who are supposed to match a balanced sample of the UK population based on that platform’s service, all the participants work at that platform, and this population may differ from actual UK participants. Lastly, these were hypothetical purchase situations, and the results may differ from those of real purchase situations. However, choice-based conjoint experiments are often used in the absence of real purchase situations and in new product development.

The third paper in this thesis is a case study on healthy food labels and technology. Case studies involve analyzing a few phenomena in depth, and this paper examined how technology-enabled labels impact the interaction between companies and consumers. This paper is still under review, and several points are essential. First, this paper attempts to create a holistic, although in-depth, analysis of how technology-enabled labels allow the exchange between companies and consumers, as the former provides more information about a product, and the latter provides more information about consumers’ changes of preference. This paper also elaborates further on the conceptual background used in this thesis compared to the previous papers. Second, this paper also showcases how the bilateral contingency model can be used to develop digitalized products and services in a consumer-oriented manner. Third, it also led to several conceptual clarifications. Conceptual clarifications were developed regarding technology and how it allows for new bilateral contingencies, such as consumer segmentation and personalized promotions, and the company's steps towards creating a marketing intelligence plan. Furthermore, healthy food labeling may be viewed as an antecedent event, initially a neutral stimulus, but it acquires discriminative or motivating functions through the explanations that people, companies, and organizations give for these labels. In the context of the marketing mix, technology-enabled labels can be viewed as a type of promotion and placement by placing different labels in different sections of a webshop. Fourth, as an example, two types of technology-enabled labels based on behavior-analytic literature that have not been investigated in depth regarding consumer behavior were used to analyze these interactions. This paper could have been more detailed and described the bilateral contingency related to digitalization, as mentioned in this introductory chapter. However, this case study is a chapter for a book on the theory of the marketing firm, a broader behavioral sciences theory related to the economic behaviors of companies and consumers. The introduction of novel technical terms related to digitalization would, at that time, not have been appropriate for that given audience.

The fourth paper in this thesis is a rating-based conjoint experiment investigating how technology-enabled labels stemming from different sources impact consumers' verbal reports of the likelihood of purchasing online groceries. This paper has been sent to different journals but rejected because it does not fit their scope and audience. First, this paper is also based on the previous paper conducted to ascertain whether these suggestions of creating self-generated labels impacted consumer behavior.

Second, this study used the same procedure regarding informed consent forms, data collection, and approval by external committees as in the choice-based conjoint experiment. Third, as in the second paper, the weaknesses of using hypothetical products may also have been present. However, the order of the introduction of the labels in this study was randomized because it did not create different models for different consumer segments. Finally, the randomization of attributes within each profile was considered, but this was not possible due to technical difficulties with the software. However, randomization of these may also have created lower ecological validity if price and delivery time had been presented in the middle of different labeling systems.

6 DISCUSSION

6.1 General Interpretation

The topic of this thesis is how the digitalization of healthy food labels can impact consumer behavior. The purpose of this thesis is to provide research that may address the problems described regarding unhealthy food consumption for society at large, companies, and consumers. This thesis argues that this phenomenon can be investigated using information systems and behavioral science knowledge. Healthy food labeling is an information systems problem consisting of transforming data regarding nutrition into information, such as labels, in an accurate manner that increases healthy food preference for consumers, could yield further profits to companies, and increase the general health of the citizens in society. At the same time, it is also a behavioral problem in that the consumption of unhealthy foods depends on the behaviors of consumers. Furthermore, digitalization processes are becoming more common in our lives, and these digital technologies broadly impact society, companies, and individuals, and are not limited to organizations that develop and use these technologies. In addition, most of the behavioral sciences and consumer behavior research focus on how thoughts, attitudes, and feelings impact healthy behaviors. An alternative approach is to study how environmental and situational variables impact consumer behavior related to healthy food. The overall topic and research question of how digitalized healthy food labels impact consumer behavior were thus asked based on this scope.

6.2 Main Findings

The main findings of this thesis are as follows. First, front-of-package food labeling can be classified into physical and digitalized static, interactive, and technology-enabled labels. More research has been undertaken on physical and digitalized static labels than on interactive and technology-enabled labels. The latter shows a promising impact on consumer behavior compared to the former two. Second, technology-enabled healthy food labels may provide consumers with personalized, dynamic, and real-time information. One consumer segment prone to unhealthy food consumption is impulsive consumers. Based on research on behavioral science regarding impulsivity, three technology-enabled food labeling systems were derived that may decrease impulsivity, and these environmental and situational variables were investigated regarding consumer choice of ordering groceries online. The results show that labels that show self-monitoring of prior healthy orders, precommitment to healthy orders with discounts, and social comparisons to healthy orders had the most to least impact on consumer behavior, in that order. In addition, minor differences were observed in that self-monitoring and pre-commitment labels were more impactful on impulsive consumers' grocery orders than non-impulsive ones. Furthermore, social comparison labels had more impact on choice for non-impulsive consumers than for impulsive consumers. Third, technology-enabled healthy food labels can emerge when companies interact with consumers. Companies may implement these labels as part of their marketing mix management. Consumers react differently based on these labels, which are a type of promotion and placement, and these labels may allow for better identification of different consumer segments and their changing preferences. This iterative process may continue for the better development of labels as well. Lastly, sources that explain different healthy food labeling systems influence consumer behavior. Technology-enabled labels allow each consumer to define what they consider to be healthy, and this may differ from public policy and retailers' definitions. Technology-enabled labels had the most to least impact on consumer behavior when the source was the consumers themselves, public policies, and retailers, respectively.

6.3 Conceptual Implications

This thesis has several conceptual implications for information systems and behavioral sciences. In particular, elements of information systems and behavioral sciences are needed to understand how digitalized healthy food labels impact consumer behavior. Regarding information systems, this thesis has implications for digital technologies, digitization, digitalization, digital transformation, and digital innovation literature (Bharadwaj et al., 2013; Hund et al., 2021; Parviainen et al., 2017; Verhoef et al., 2021; Vial, 2021; Warner & Wäger, 2019; Wessel et al., 2021). Specifically, it does so by investigating how these literatures can be used to understand digitalized healthy food labeling. This thesis proposes that healthy food labeling is an information system that transforms data into information by providing simplified symbols or logos regarding the health aspects of products. It also proposes how digital technologies and processes related to digitalization can be used to understand digitalized healthy food labels. The implications are that digital technologies and processes can account for changing labeling requirements, making companies and information systems more flexible. Specifically, focusing on digital technologies that generate value in extended interfirm networks could benefit retailers when labeling requirements change or when new labeling systems are demanded. Additionally, the use of digitalized healthy food labels could lead to digital transformation and digital innovation for some companies in some specific circumstances. For instance, each digitalized healthy food label will have data associated with it and its relationship to consumer behavior. This data may later be recombined and assessed in the context of other products or services. For instance, a healthy food-focused online grocery store could have data related to the social comparison label and data on the purchase of fair-trade products. Companies could then, based on correlational and predictive analyses, decide to combine these features in a label showing by how many fair-trade products a consumer's basket differs from the average consumer and evaluate whether consumers prefer this system. If they do, then the online store could gradually implement new labeling systems and shift its business model to a broader sustainability marketing. Digitalized healthy food labels could also be a platform for digital innovation, either by digitalization or digital transformation. That is, it could do so by testing out novel digitalized healthy food labels and their impact on consumer behavior, or analyzing this relationship in the context of other information and changing strategic models. Additionally, digital technologies may provide new environments for one actor or connect several actors, which may impact their behavior.

Regarding behavioral sciences, this thesis has implications for conceptualizations related to healthy food choice (Glanz & Bishop, 2010; Liu et al., 2014; Roberto & Kawachi, 2014), healthy food labeling (An et al., 2021; Hersey et al., 2013; Ikonen et al., 2020; Temple, 2020), consumer behavior analysis (Foxall, 2016; Foxall, 2017), the bilateral contingency model (Foxall, 1999; Foxall, 2021), impulsivity (Rung & Madden, 2018), and rule-governed behavior (Harte & Barnes-Holmes, 2021; Pelaez, 2013; Peláez & Moreno, 1998). That is, the implications are that there exist several ways of increasing healthy food choices and that one strategy is to provide simplified information related to healthy food rather than providing more information to consumers. It also investigates how consumers respond to these labels by investigating environmental and situational variables. These events can be directly altered, and their impact on behavior may be assessed rather than relying on relationships that cannot be altered, such as cognition, attitudes, beliefs, and so on. Additionally, new environment-behavior contingencies may be arranged by the use of digital technologies. The latter implies that prior research on behavior-environment contingencies in laboratory contexts can be used in unexplored applied research settings, such as when it comes to healthy food choice. It also has implications for how information systems change behavior by the use of environmental or situational variables. Specifically, information systems convert data into information through processing. Hence, data are stimuli that do not impact behavior are being processed into stimuli that do impact behavior. In information systems literature, these are referred to as "information," while in consumer behavior analysis, these are referred to as consequences and antecedent events, depending on how they impact behavior. Moreover, healthy food labels are antecedent events that change consumer behavior depending on rules or instructions. That is, labels change behavior depending on how they are explained to the consumers in describing how products get these labels. Lastly, it extends research on consumer behavior by investigating impulsivity and rule-giving in the context of emerging technologies.

The conceptual implications provided by the individual papers are as follows. First, the systematic review contributes to a classification for studying digitalized labels in terms of whether they are static, interactive, or technology-enabled, in addition to identifying previous research on the topic. Second, it also has methodological contributions in the second paper on identifying impulsive consumer segments and investigating which promotion of healthy food products is effective for them. The implications of this research contribute to consumer behavior analysis, research on impulsivity, and the digitalization literature, viewed in the sense that some technologies may bring value not only to specific entities and organizations but also have broader impacts, such as societal and consumer impacts. Impulsive consumers are a vulnerable consumer segment, and research on this could help address societal issues. Third, an example of how to use the bilateral contingency model was used in the context of developing technology-enabled labels. This has implications for research on bilateral contingencies, as few have investigated healthy food labeling, particularly digitalized healthy food labeling, using this conceptual framework. Fourth, it also has implications for healthy food labeling research and consumer behavior analysis in that symbols or logos acquire their function on consumer behavior based on the explanations of these labels, and different sources or definitions impact how consumers react to them. Finally, this research has implications for a broader understanding of digitalization processes and how consumers shape companies' digitalization strategies.

6.4 Implications for Practice

The individual studies have several implications for practice in terms of society, companies, and consumers. The systematic review results show increased research on digitalized front-of-package food labeling and indicate that technology-enabled labels could be promising in helping consumers select healthy foods. In addition, identifying effective digitalized labels could reduce unhealthy food consumption, which may help reduce obesity, economic costs, and human suffering. For companies, it may provide retailers and brand owners with a competitive advantage by presenting more accurate information, selling healthier products, and gaining positive word-of-mouth. For consumers, the labels may increase the value of healthier food products and attract new shoppers. The choice-based conjoint experiment also has implications for companies and consumers. Based on these findings, companies may use self-monitoring labels rather than providing labels offering a discount of 10% for current and future healthy food promotion. They may not be that costly to implement, and they may be integrated into online grocery stores' consumer accounts. Furthermore, negative social comparison labels did not negatively impact consumers' choices, indicating that such labels are not detrimental to purchasing food products. However, a positive social comparison label was associated with a higher likelihood of choosing such a product than negative labels, and retailers could still use these to promote healthy food products. Such labels could generate more engagement with the online store, which may also be of value to online grocery stores and could generate more revenue. However, companies must also consider what information is being processed by using such labels and evaluate their risk regarding privacy, accurate data, accessibility, and ownership (Rainer & Prince, 2021). The conceptual paper demonstrates the process of consumer-oriented strategies that companies can use to generate more profit, revenue, and a better reputation in the context of technology-enabled labels. The development of two proposed labels was analyzed in the context of marketing research, marketing intelligence, and marketing mix management. Specifically, marketing research strategies could first be explored before implementing these labels. Later, integrating these labels into marketing intelligence systems may better equip companies to identify different consumer segments and changing preferences. Lastly, marketing mix management of healthy foods related to the product, promotion, price, and placement was analyzed. These labels may be viewed as a type of promotion, but also allow for novel placements compared to physical labels. The developments, methods, and analyses were suggested at each step, directly impacting online grocery stores. The rating-based conjoint paper found that technology-enabled labels, when defined by the individual consumer deciding to purchase, were more impactful on the likelihood of purchase than when defined by public policy implementations or online grocery stores. In addition, consumers' selection of products they perceive as healthy differs from what the Eatwell Guide states, which is a UK public policy recommendation for eating healthy foods (Public Health England 2018). This has direct implications for society, companies, and consumers as they operate with different definitions of what they consider healthy products. In addition, this research has implications for consumers' needs, as most consumers stated that they would react positively if they saw these labels in real online grocery stores.

These findings also have implications for prior approaches such as regulations, taxation, subsidizing, nudging, marketing, and front-of-package labeling of food products. In particular, public policy-based food labeling can also be presented using digital technologies. As mentioned by Fuchs (2022), regulations exist related to presenting the nutritional content of food products online, which could happen through digital labeling of food products. Regarding nudging strategies, these studies did not use direct conceptualizations based on nudging, although several of these technology-enabled labels could fall under that category. In particular, some of these labels did not restrict consumers' choices or change economic incentives to do so. For instance, self-monitoring, social comparison, and labels defined by individual consumers who make the purchase decision, as well as stores and public policies, did not restrict consumers' choices or change economic incentives. However, the pre-commitment label, which was based on discounts, altered economic incentives for consumers. These labels were analyzed in the context of marketing strategies using the marketing mix in the conceptual paper. Finally, front-of-package food labels, using digital technologies, were investigated in the systematic review.

6.5 Limitations

These findings should be considered in the context of the study's topic, scope, and methodological limitations. First, this thesis did not undertake field or laboratory experiments directly investigating the effects of digitalized static, interactive, and technology-enabled labels on consumer behavior. Second, this thesis mainly focused on technology-enabled labels and did not investigate interactive and static labels. Third, both conjoint experiments consisted of participants who evaluated hypothetical purchase situations, and future research should investigate these in real purchase situations. Furthermore, individual papers did not elaborate further on digitalization processes from the perspective of operant systems. In addition, although relevant, this research did not directly investigate the context of these labels concerning other previously attempted solutions, such as regulations, taxation, subsidizing, and nudge theory, in depth. Other conceptual frameworks and variables, such as other behavioral science conceptualizations and consumer privacy concerns, were not directly investigated. Lastly, this thesis did not perform empirical studies on the broader relations between digitalization processes that companies employ and how consumers shape them.

6.6 Ethical Considerations

Several ethical considerations exist regarding digitalized labels and their impact on consumer behavior. This thesis focuses on soft approaches rather than hard approaches. Imposing strict and hard approaches restricts people's behavior, and digitalized labels can promote healthy foods without doing this. Furthermore, it is important that organizations that implement these labels do so in a way that is accurate and transparent, which is of interest to consumers and society. As mentioned, healthy food labels may have a halo effect. The transformation of nutritional data into a healthy food labeling system may simplify some details. Thus, consumers should be able to acquire more information regarding a product if they wish, such as detailed explanations of what labels do. In addition, there may be security risks of prior purchases that could be traced back to individual consumers and other parties using this information without the consent of the consumers. Building on this, consumers should also be able to decide what information they are being presented with in online stores, including the option to opt out. Several considerations were taken to ensure that this research was ethical. First, all experiments consisted of giving participants an informed consent form and ensuring that they could stop at any time without negative consequences. Participants were paid even if they did not finish the studies. Second, SIKT, the Norwegian Agency for Shared Services in Education and Research, was contacted during all the experiments. Third, personally identifiable data were processed by the platforms used to recruit and collect responses from the participants, but we did not collect this data. As a result, the experiments minimized asking for personally identifiable information, and those that can be considered personally identifiable were aggregated such that it is impossible to trace these individuals.

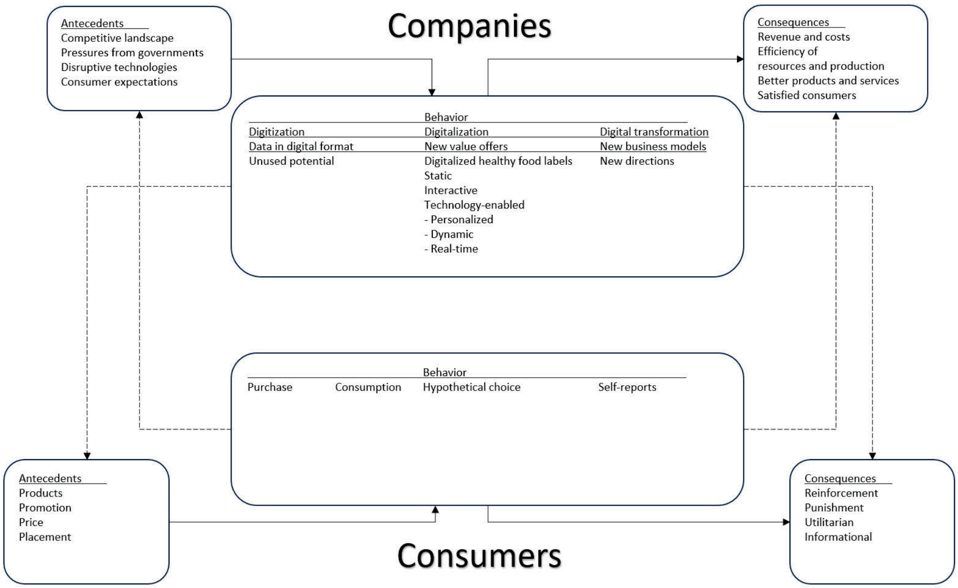
The negative impact of digitalized healthy food labels on consumer behavior is also worth mentioning. When it comes to consumers, digitalized food labels may contribute to halo effects, privacy issues, more consumer confusion when more label systems are introduced, more pressure on consumers to be aware of their food choices, which may increase stress, and some labeling systems may provide too much information to consumers. However, these negative impacts could be reduced if opt-out options were given to consumers or where consumers have the possibility to shop at other providers that do not employ these. When it comes to companies, the presence of such labels may influence them in that companies may build labels that produce more profit over actual healthier food choices, that cost may increase when companies conduct digital innovation, consumer discrimination in the form of personalization may produce unfortunate ethical consequences, that small companies cannot compete with large ones, and that more information about consumers leads to greater damages if data breaches were to occur. However, companies may consider these when developing digitalized healthy food labels and ensuring that these risks are minimized. When it comes to society, there may be several negative impacts of digitalized healthy food labels. First, some of these labels may not respect local traditions in that some foods are considered healthy based on their social aspects rather than nutritional aspects. For instance, ingredients essential to the Mediterranean diet may be more negatively labeled than other ingredients based on their nutritional profile, as they may contain more food oils compared to other diets. However, eating traditional foods together with others may be healthy in the sense that it promotes social well-being. Second, digitalized food labels may create a larger digital competency gap. That is, certain populations like elderly individuals may not have the skills or prior training to use digitalized food labels effectively. However, such labels may be developed in a user-friendly manner such that they also accommodate these populations. Lastly, classifying whether something is healthy also has political aspects to it. Many actors are involved in this, and some actors are dramatically impacted by whether certain foods are labeled as healthy. The scope of this thesis consists of how digitalized healthy food labeling impacts consumer behavior, and some points were made regarding what counts as healthy foods or diets. However, the main emphasis of this thesis is how symbols or logos that are otherwise neutral impact consumer behavior when they highlight how healthy the food is through the use of digital technologies.

6.7 Future Research

Future research should investigate how consumers generally shape digitalization processes. More specifically, the companies' behavior related to digitalization, consumer behavior, and digitalized healthy food labels can be analyzed by their antecedent events and consequences (as shown in Figure 5). The company may perform several behaviors related to developing and using digital technologies. These may be broadly classified as digitizing, digitalization, and digital transformation. The consequences of these behaviors may include changes in revenue or decreased costs, efficient use of resources and production, new or improved products or services, or more satisfied consumers (Mergel et al., 2019; Verhoef et al., 2021). The antecedent events of these behaviors may include competitive landscapes, pressures from governments, the presence of disruptive technologies, and consumer expectations (Mergel et al., 2019; Verhoef et al., 2021; Vial, 2021). In addition, these technologies could, in some circumstances, lead to digital transformation and digital innovation.

Figure 5

The Digital Bilateral Contingency Model



Note. This figure illustrates a digitalized bilateral contingency between two digital operant systems in terms of digital technologies and the three-term contingencies for companies and consumers individually (solid lines) and the bilateral contingencies (dotted lines).

Physical or online grocery stores can use several digitalization behaviors. Digitalization behaviors consist of implementing digital technologies and the mentioned technologies can be implemented in general retail (Shankar et al., 2021), grocery retail (Inman & Nikolova, 2017), online stores (Fagerstrøm et al., 2022; Fagerstrøm, Eriksson, et al., 2020; Sigurdsson et al., 2024; Valenčič et al., 2022; Wyse et al., 2021), and in the context of digitalized static labels (Antúnez et al., 2015; de Alcantara et al., 2020; Hagmann & Siegrist, 2020; Miklavec et al., 2021) interactive labels (Finkelstein et al., 2019; Finkelstein et al., 2021; Fuchs et al., 2022; Sacks et al., 2011), and technology-enabled labels (Braga et al., 2023; De Bauw et al., 2022; Shin et al., 2022; Shin et al., 2020).

Some of these company behaviors resulted in changes in several of the consequences described. For instance, Inman and Nikolova (2017) state that QueVision, a type of digital technology, has increased revenue by reducing shopper waiting time at the checkout and increasing shopper satisfaction. Another example involves Shankar et al. (2021), who state that delivery technologies have improved companies' ability to track deliveries and enable consumers to return their orders more effectively. Regarding revenue and costs, Wyse et al. (2021) found no change in revenue and costs between intervention and control based on six studies. They suggest a more explicit investigation into the cost-effectiveness of these interventions. However, these results may depend on what information is enabled by digital technologies to promote healthy food. For instance, Fagerstrøm et al. (2020) found that all Internet of Things-enabled information creates a higher likelihood of buying fresh salmon from a smartphone app than traditional information. Similarly, Fagerstrøm et al. (2022) found that higher consumer ratings on taste and healthiness had more impact on the likelihood of buying groceries for a barbecue party than lower ratings. Likewise, Sigurdsson et al. (2024) found that digital quality signals, such as product ratings by other consumers, had more impact on the choice of fish purchase than the quantity sold online. Regarding efficiency of resources and production and better products and services, digital technologies to promote healthy foods may be used to standardize specific processes such as marketing research and intelligence regarding products, better identification of what consumers value the most when it comes to purchasing healthier products, and companies may be able to charge a premium for that service. Regarding satisfied consumers, Braga et al. (2023) conducted an online experiment, presenting a technology-enabled label based on the virtual basket consisting of different scores, including one on how healthy the products in the basket are. More than half of the participants later stated that the online grocery store was better than past online stores. Similarly, satisfied consumers may affect the information delivered by digital technologies, such as consumer product ratings (Sigurdsson et al., 2024) and health and taste (Fagerstrøm et al., 2022).

Some of the company's behaviors occurred in the presence of several antecedent events. For example, Shankar et al. (2021) state that Amazon Go stores, which use digital technology to create cashier-less shops, have driven retailers to consider using this service, which is relevant for social distancing in terms of COVID-19. Inman and Nikolova (2017) suggest that Costco could give consumers the option to access their shopping history, which could allow them to create their shopping lists and allow suppliers to bid on the option that their products are listed at the top. Regarding the competitive landscape, more consumers have shopped at online stores since the COVID-19 pandemic, but some product quality signals in physical stores (e.g., smell) are different in online stores. Retailers are now actively trying to identify several digital quality signals (Sigurdsson et al., 2024). Furthermore, some digital technologies can be a deal-breaker in a competitive market, as some consumers prefer combinations of traditional and Internet of Things-enabled information in online grocery stores (Fagerstrøm, Eriksson, et al., 2020), while other studies found that digital technologies that present healthy product labels by using quick-response codes could be a good investment for retailers, especially in a highly competitive market (Fagerstrøm et al., 2022). Regarding pressure from governments, Wyse et al. (2021) state that digital food environments provide opportunities to deliver strategies to improve public health, which initiated their research on the topic, while Fuchs (2022) argues that some digitalized labels may become mandatory in the future for online grocery stores. In the context of disruptive technologies, Sigurdsson et al. (2024) found that product rating influences consumer choice the most. Implementing this digital technology may lead to disruptive effects for retailers and brand owners, as the retailer or brand owners cannot control this information. One strategy involves avoiding such implementation if there are few very dissatisfied consumers, and such ratings may initially be variable and will stabilize over time as more consumers rate products. Furthermore, regulations exist today on declarations of nutrients for groceries sold online, and advancements in recognizing these may lead to unpredictable digital technologies that may affect how companies promote healthy food products (Fuchs et al., 2022). Related to consumer expectation, Valenčič et al. (2022) suggest that understanding decision-making in digital environments is becoming more important as more consumers are expected to do grocery shopping online.

Lastly, phenomena from consumer behavior analysis could also be further explored, such as research on impulsivity, rule-governed behavior, and behavioral variability, which can be used in the context of digitalized healthy food labeling. Specifically, other factors related to impulsivity, such as temptation bundling, situation modification, goal-setting, making the future self-relatable, contingency management, time framing, framing of outcomes, priming, adding delays, and modeling (Duckworth et al., 2018; Rung & Madden, 2018; Scholten et al., 2019) of healthy food choice in combination with digitalized healthy food labels could be explored.

Regarding rule-governed behavior, other aspects related to rules (or instructions) such as tracks, plys, augmentals (Zettle & Hayes, 1982), explicitness, accuracy, complexity, and source, and delay (Pelaez, 2013; Peláez & Moreno, 1998) could be used to analyze how descriptions of healthy food labeling systems impact the effectiveness of such symbols or logos on consumer preferences and how novel digitalized healthy food labels also impacts preferences. When it comes to behavioral variability, empirical investigations of digitalized healthy food labeling that promotes behavioral variability and its impact on consumer preference should be conducted. For instance, behavioral variability procedures, such as frequency-dependent, threshold, and Lag n schedules procedures (Nergaard & Holth, 2020), could be integrated into digitalized healthy food labeling related to consumers' prior healthy food choices.

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Review

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Effects of Digitalized Front-of-Package Food Labels on Healthy Food-Related Behavior: A Systematic Review

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Abstract: Front-of-package (FOP) food labels may impact healthy food-related behavior. However, such labels may be presented using new technology and they may impact behavior differently than physical labels. This systematic review investigated the effects of physical and digitalized labels on healthy food-related behavior. This review used four search engines to collect articles that investigated the effects of food labels on the purchase, consumption, hypothetical choice, and self-reports of healthy foods. General findings, types of labels, or whether the articles used physical versus digitalized static, interactive, or technology-enabled labels were synthesized. The dependent variables were categorized according to whether they were under full, partial, or no control of the independent variables. The risk of bias was measured by the RoB 2 tool and adapted Joanna Briggs Institute Checklist. The search strategy identified 285 records and 30 articles were included. While digitalized static and physical labels did not differ in their effects on healthy food-related behavior, technology-enabled labels were more predictive of healthy food-related behavior than interactive labels.

Keywords: food labeling; consumer behavior; healthy foods; physical labels; digitalized labels; technology

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1. Introduction

Consumption of unhealthy foods is a major societal problem despite numerous efforts by different institutions and organizations. Obesity has approximately doubled worldwide since the 1980s [1]. Research shows a connection between the consumption of unhealthy foods and an increased risk of heart disease [2]. In addition, it is even associated with an increased risk of suicide attempts [3]. Furthermore, it is also an economical burden for society. A high body mass index is estimated to cost USD 990 billion per year globally for healthcare services [4]. Using mandatory nutritional labels on food products is only one of many proposed interventions. It may have ameliorated the rising epidemic of obesity. However, this may not be the case for all subgroups of consumers, such as individuals who are already obese [5]. As a result, the World Health Organization [6] suggests that the food industry should promote healthier diets by providing simple and clear food labels. This can be achieved by presenting simplified front-of-package (FOP) food products. Several types of FOP food labels exist, as shown in Figure 1. However, research shows that the effects of these FOP food labels on healthy food-related behavior are inconsistent and vary in relation to which type of behavior is measured [7–12].

Technology may be used to present digitalized FOP food labels in novel ways, and such labels may be more effective than physical labels. Digitalized FOP food labels may be static, interactive, and technology-enabled. Interactive technology may provide detailed product information to consumers, and technology-enabled retailing may provide personalized products for each consumer, dynamic presentations of products that may be changed based on previous purchase history, and provide real-time information where such offers are given immediately [13,14]. These characteristics may be used for digitalized FOP food labels.

For instance, Shin et al. [15] presented digitalized FOP food labels in order to study their effect on healthy food purchases. The label presented an overall healthiness score based on foods in the virtual basket of each consumer in an online grocery store experiment. They found that such digitalized FOP food labels increased healthy food purchases. Physical FOP food labels are static labels that are presented on the physical package, menu boards, or shelf tags near the products in physical stores. Digitalized FOP food labels are presented mostly in online grocery stores by a medium or device. In this situation, digitalized FOP food labels are presented together with images of the food product and may be in the form of static, interactive, or technology-enabled. Digitalized static FOP food labels are similar to physical FOP labels as they also present a static image of the food label but differ as they are presented through a medium. Interactive FOP food labels provide additional options to access more information regarding the health aspects of the food product or the label. Technology-enabled FOP food labels provide personalized, dynamic, and real-time information. Specifically, such labels can provide personalized information based on each consumer, dynamical information based on their specific actions with the medium, and real-time information to the consumers. Hence, physical, digitalized static, interactive, and technology-enabled FOP food labels may present different information to consumers, as shown in Figure 2, and these may influence healthy food-related behavior in different ways.

Figure 1. The figure shows examples of different types of front-of-package food labels. From top left to right, a single summary label (Nordic Keyhole), graded summary label (French Nutri-score), and combined label (Australian Health Star Ratings) are shown. A percentage-based nutrient-specific label (British Guideline Daily Amounts), single nutrient-specific label, and graded nutrient-specific label (British Traffic Lights) are shown from bottom left to right.

Healthy food-related behavior may be measured in several ways and FOP food labels may impact these behaviors differently. Healthy food-related behaviors can be categorized into purchase, consumption, hypothetical choice, and self-reports regarding healthy foods. Purchase may be measured by actual money spent on foods, consumption in terms of the number of calories consumed, and hypothetical choices may be measured by a relative selection of a product given a set of several products without actually owning or consuming the item in the presence of a question. Self-reports are verbal estimations of participants′ own behavior toward a given product in the context of other questions and may be used to study consumer behavior in general (see [16] for different measurements of consumer behavior related to FOP food labels). FOP food labels may affect one or several of these measurements. For example, the purchase of foods may be influenced by FOP food labels, although with either small or inconclusive results [7], consumption may be influenced by different FOP food label types [10], hypothetical choices may also be impacted by these FOP food labels [17], and self-reports such as participants ratings of healthfulness [18], taste [19], trustworthiness, intent to purchase [20], affect and familiarity [21] related to healthy foods may also be influenced by FOP food labels.

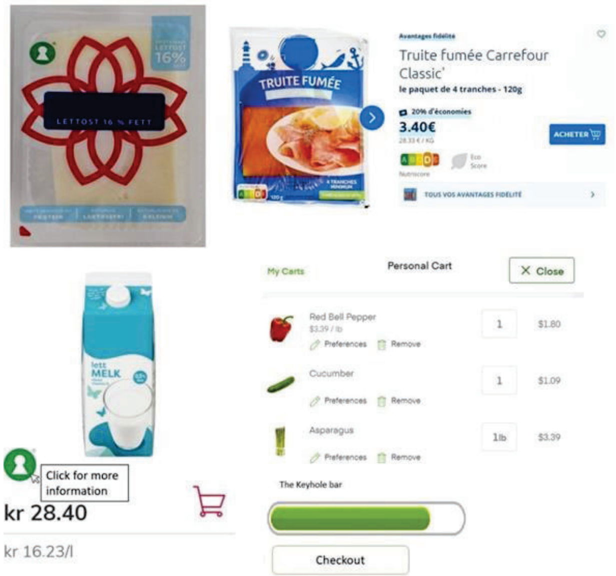

Figure 2. The figure shows hypothetical examples of physical (upper left), digitalized static (upper right), digitalized interactive (lower left), and digitalized technology-enabled (lower right) front-of-package food labels.

Although there exists extensive research on related topics, few literature reviews exist on the effects of digitalized FOP food labels on healthy food-related behavior. For instance, there exists research on health-related information delivered by technology in physical stores [22] and the effects of health labels and ingredient labels on consumption and self-reports [23]. Furthermore, Granheim et al. [24] did a systematic scoping review regarding the digital food environment and identified some articles which have examined the impact of healthy food labels on healthy food-related behavior in an online grocery setting without comparing their effects to physical FOP food labels. Similarly, Pitts et al. conducted a review on the promises and pitfalls of online grocery shopping related to healthy food purchase [25]. However, to the best of our knowledge, no systematic literature review has examined the effects of physical and digitalized FOP food labels regarding different types of labels and their effect on healthy food-related behavior. Knowledge of such effects on healthy food-related behavior has both academic and social importance. First, such research provides an understanding of how technology in this setting influences human behavior, health-related behavior, and consumer behavior. Second, such knowledge may aid in reducing obesity, economic costs, and human suffering worldwide. Finally, knowledge regarding digitalized FOP food labels may give brand owners and retailers a competitive advantage [26]. Specifically, digitalized interactive and technology-enabled FOP food labels may provide more accurate descriptions regarding products and present personalized, dynamic, and real-time information on health scores to consumers. This may increase the value of healthy foods while at the same time benefiting brand owners and retailers by increasing the number of healthy food purchases, attracting new customers, and increasing positive word-of-mouth [27]. This paper aims to fill that knowledge gap by presenting a classification system of physical and digitalized FOP food labels and investigating how such labels impact consumer behavior through a systematic review. The objective of this paper is to investigate how physical, digitalized static, digitalized interactive, and digitalized technology-enabled FOP food labels impact purchase, consumption, hypothetical choice, and self-reports regarding healthy foods.

The rest of the paper is structured in the following manner. First, previous research regarding the classification of FOP food labels and studies that have investigated physical labels, and digitalized static, interactive, and technology-enabled labels is presented. This is followed by providing the methods used in this review. The result of the review is then presented. Discussion of the results in light of previous research is then provided. At last, further research directions are suggested.

2. Literature Review

FOP food labels can be classified as summary labels, nutrient-specific labels, or combinations of both [9] as shown in Figure 1, and their effects may be moderated by other variables. Summary labels present an overall health evaluation of a food product and may be presented as single or graded summary labels. Single summary labels are binary and their presence on a food product indicates that the product is considered healthy; an example is the Nordic Keyhole [28]. However, graded summary labels present a score between a minimum and a maximum value as a higher score corresponds to a higher degree of the healthiness of a product, such as the French Nutri-Score [29]. In contrast, nutrient-specific labels present some key nutrients on the front of the package and specify the degree of the healthiness of specific nutrient contents. Nutrient-specific labels can be presented in terms of percentage-based, single, and graded nutrient-specific labels. Percentage-based nutrient-specific labels show a percentage that is based on specific nutrient content or recommended daily intake based on an average adult. Single nutrient-specific labels are binary and show an excess of a given nutrient. Graded nutrient-specific labels show the nutritional content such as "low", "medium", or "high" amounts. Guideline daily amounts [30] warning labels [31], and traffic lights [30] are examples of nutrient-specific labels. Some FOP food labels use combinations of summary and nutrient-specific label elements such as the Australian Health Star Rating system [32]. In addition, several other independent variables that influence the effectiveness of these labels have been investigated, such as color-based labels [8,12], time-pressure conditions, nutritional knowledge about labels [11], textual claims [33], and self-control [34], among others. In short, FOP food labels can be categorized in summary, nutrient-specific, and combined labels with several different subcategories and other variables in combination with labels have been investigated.

Physical FOP food labels and their effects on healthy food-related behavior have been examined by other researchers. Roberto et al. [19] allocated participants randomly in a campus store context to no FOP food label, combined FOP food label, and combined FOP food label with additional per serving information conditions. These labels were presented for a cereal and the study measured participants' self-reports regarding estimations of calories, total sugars, vitamins, healthfulness, intent to purchase cereals, total grams poured, and total grams consumed. Participants allocated to the combined FOP food label per serving condition had higher self-reports regarding estimations of calories. In contrast, other healthy food-related behavior measurements did not differ between the conditions, indicating no effect. Similarly, Julia et al. [35] allocated participants in a controlled lab store context to no FOP food label, graded summary FOP food label, and graded summary FOP food label with information regarding the criteria of the labels, and these were presented for different food products. The study measured the mean nutritional qualities of the food items participants had selected in their shopping carts and used self-reports regarding the recall of the labels, healthfulness, and understanding. The results show that there were few differences between healthy food-related behavior as a function of these FOP food labels on hypothetical choice, but that they impacted self-reports regarding recall and understanding. Koeningstrofer et al. [34] conducted two studies regarding the effects of nutrient-specific FOP food labels on healthy food-related behavior. In the first study, participants in a controlled laboratory store context were allocated to no FOP food label. Participants in the nutrient-specific FOP food label conditions were instructed to shop for four items. The process measured participants' purchases and self-reports regarding self-control and used professional dieticians to classify which foods were considered healthy. The second study extended the previous study by using a standardized healthiness of food product scale instead of ratings of dieticians. The results of both studies show that participants who had lower self-reports regarding self-control were correlated with a larger decrease in unhealthy food purchases when the label was present, while participants with higher self-reports regarding self-control were correlated with smaller effects when the label was present. Hence, in regard to the effects of physical FOP food labels, one article found differences regarding purchases when self-reports regarding self-control were high [34] one article did not find different effects on hypothetical choices [35], one article did not find differences in self-reports [19], and one article found different effects regarding self-reports [35].

Digitalized static FOP food labels and their effects on healthy food-related behavior may differ from physical FOP food labels. For instance, digitalized static FOP food labels may be presented at several locations in the online grocery retail setting, such as on the first webpage in context with other products or on the second webpage when the product is presented alone and together with the nutritional information labels of that product. Digitalized static FOP food labels may be enlarged and may take up more space with the food product image than physical labels. In addition, there is a longer delay between the purchase and consumption of food products in the presence of digitalized FOP food labels compared to physical FOP food labels. Talati et al. [17] conducted a large-scale online experiment with participants across 12 countries to study the effects of combined, graded nutrient-specific, percentage-based nutrient-specific, graded summary, single nutrient-specific, and no FOP food labels on hypothetical choice. Participants were exposed to food products with no FOP food label, were instructed to select which one out of three products they would like to purchase, and were again presented with the same products in combination with one type of FOP food label. Their results show that the hypothetical choice regarding healthy foods was improved from most to least by graded summary, graded nutrient-specific, single nutrient-specific, combined, and percentage-based nutrient-specific FOP food labels. Similarly, Raats et al. [36] conducted an online experiment with participants from 6 different countries and investigated the effects of percentage-based nutrient-specific labels based on "per 100g" and "typical portion size" in combination with different food products on self-reports regarding the healthfulness of products by categorizing products on a scale from most to least healthy. Their results show that these labels produced different results. For instance, products in combination with labels based on "per 100g" were rated less healthy than "typical portion size" labels. At last, Khandpur et al. [37] investigated the effects of single nutrient-specific and graded nutrient-specific labels on hypothetical choices and self-reports regarding the intention to purchase, nutritional accuracy, and ratings of the healthfulness of food products. Their results show that participants exposed to single nutrient-specific labels had a higher hypothetical choice and self-reports regarding nutritional accuracy, and lower self-reports regarding healthfulness than graded nutrient-specific FOP food labels. Hence, in regard to the effects of digitalized static FOP food labels, two article found differences in hypothetical choice [17,37], and three articles found differences in self-reports regarding the healthfulness of products [36,37].

Digitalized interactive FOP food labels and their effects on healthy food-related behavior have been investigated, although less than digitalized static FOP food labels, and they may also impact healthy food-related behavior differently than other labels do. For instance, consumers could get more information about the product's nutritional information or how such labels grade a given food product. In addition, the location of options such as a button on the first screen or the second screen could also influence healthy food-related behavior. Furthermore, there exists research that has examined the effects of digitalized interactive FOP food labels. Egnell et al. [38] investigated the effects of graded summary, percentage-based nutrient-specific, and no FOP food labels on hypothetical choices in an online grocery context. Interestingly, participants in that study had the option to access more information regarding the labels or the food product by clicking a specific button. Participants' hypothetical choice regarding healthy foods was higher when exposed to graded summary labels than to percentage-based nutrient-specific labels. No label produced the least hypothetical choice regarding healthy foods. Maubach et al. [39] investigated the effects of graded summary, graded nutrient-specific, percentage-based nutrient-specific, and no FOP food labels on best-worst scaling in a choice experiment. Similarly, participants could get more information regarding nutrients, ingredient lists, and allergens by clicking on a specific button. Their results show that graded nutrient-specific labels had the most impact on hypothetical choices than other conditions. Andrews et al. [40] examined single summary labels, graded nutrient-specific labels, and no FOP food labels on self-reports regarding the healthfulness of the product and nutrient estimations of food products. The participants could click on a button to see nutritional labels on the back of the products. Their results show that graded nutrient-specific labels generated higher nutrient accuracy than did single summary labels. Single summary labels generated higher self-reports regarding healthfulness than the other conditions. Sacks et al. [41] examined the impact of graded nutrient-specific labels and no FOP food labels on purchase. Likewise, the participants were presented with the FOP food labels and could get more information about the labels or nutritional information by clicking on a specific button. Their results indicate that introducing these FOP food labels did not change overall purchases nor sales of products without "red labels." Fuchs and colleagues [42] investigated the effects of interactive FOP food labels on purchase and self-reports of healthy foods in a laboratory-based online grocery store. Specifically, they developed a Google Chrome extension that displayed Nutri-Score for product-specific food products. Their result shows that individuals that were exposed to such static labels purchased on average, more healthy food products than did controls. In addition, the effect was stronger for individuals with low food literacy and individuals that were exposed to such labels showed stronger advocacy for introduction of such labels. Hence, one article shows that digitalized interactive FOP food labels did not influence purchase [41] while one article found an increase in purchase [42], two articles show that digitalized interactive FOP food labels influenced hypothetical choices [38,39], and two articles show that digitalized interactive FOP food labels influenced self-reports of healthy foods [40,42].

Digitalized technology-enabled FOP food labels and their effects on healthy food-related behavior have not been investigated in as much detail as physical or other digitalized FOP food labels. For instance, one could arrange a digitalized technology-enabled FOP food label that presents an overall graded summary label as a personalized, dynamic, and real-time based progress bar based on all products within a virtual basket before or during purchase. Such a progress bar may display how healthy a food shopping cart is or how unhealthy a virtual food cart is. As indicated elsewhere [43], such framing may influence food purchases. However, few articles have investigated the effects of digitalized technology-enabled FOP food labels on healthy food-related behavior. Shin et al. [15] investigated the effects of aggregated dynamic food labels with real-time feedback based on food products in each consumer's virtual basket, and presented the result as a pie chart based on graded summary FOP food labels or based on graded nutrient-specific FOP food labels, in combination with an option to sort products selected by consumers from most to least healthy on consumers food selection. The study used a crossover design. Half of the participants completed grocery shopping first without the dynamic food label and then with the dynamic food label. The other half completed shopping first with the label and then without the label. The participants who were exposed to the labels could select which one of seven different types of FOP food labels they would like to see. The study results show that participants exposed to the aggregated dynamic real-time food label scores selected on average, foods with a higher Nutri-score value, lower amounts of total sugar, and lower calories than those not exposed to such FOP food labels. Hence, one article [15] showed that digitalized technology-enabled FOP food labels increased healthy food choices.

3. Materials and Methods

The procedure for conducting this systematic review was based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [44].

3.1. Eligibility Criteria

The articles which were included were (a) peer-reviewed journal articles and books, (b) empirical research articles which presented new data, and (c) written in English. With regard to (d) the first screening phase, articles that had the following text in the title, abstract, or keywords: "cues", front-of-package", "labels", "point-of-decision", "symbols", "icons", and "logos" and its effect on food-related behaviors were eligible for the final screening phase. After the search, the following variations of the terms were included in order to avoid ambiguity: "cue", "label", "package", "packaging", "icon", and "logo". Regarding (e) the final screening phase, the articles included in this review were based on the full text of the article and included if they investigated FOP food labels on healthy food-related behaviors. FOP food labels were defined as a single summary, graded summary, percentage-based nutrient-specific labels, single nutrient-specific labels, graded nutrient-specific labels, or combined labels. Healthy food-related behaviors measured participants' purchases, consumptions, hypothetical choices, and self-reports related to healthy foods measured quantitatively. After the search, self-reports were defined by being assessed on a Likert-type scale. Healthy food was defined as either low in sodium, saturated fats, sugar, or calories, or with an excess of protein, unsaturated fats, fiber, or vitamins. Conference articles, other sources, conceptual articles, literature reviews, articles that used secondary data, non-English articles, and articles that violated the first and final screening criteria were excluded.

3.2. Search Strategy

Studies were identified using search engines for academic peer-reviewed journal articles, and the search engines selected were based on the findings by Gusenbauer and Haddaway [45]. The principal search engines that were used for this study were "Web of Science", "Science Direct", "PubMed", and "Wiley Online Library." The search was performed, and information regarding articles was extracted on the 8 of November 2021. The search consisted of identifying possible eligible articles using the following search string: "front-of-package" AND ("technology" OR "online grocery"). The same search string was used in all the search engines. In addition, no filters were used during the search in all search engines. There were no imposed restrictions on publication dates or journal categories. The search process consisted of extracting the reference information for possible eligible articles by clicking on the "export" option for each search engine and downloading an article information file. The files contained the following information name of the journal, year of publication of the article, author(s) of the article, title of the article, the abstract, and keywords for each article.

3.3. Selection Process

These article information files from the four databases were merged into one common file. Two independent reviewers screened the articles listed in the common article information file based on the eligibility criteria. The reviewers had inter-rater reliability of 85.23% agreement in the first screening phase. The two reviewers resolved disagreements by discussing which eligibility criterion was violated, followed by a reassessment. If the meeting did not result in an agreement, then a third independent reviewer provided a final assessment of whether the article met the eligibility criteria. The reviewers had inter-rater reliability of 72.72% agreement in the final screening phase. Similarly, disagreements for the final screening phase were performed by two independent reviewers, and a final assessment by a third if there were disagreements. The consensus of the two reviewers resolved all disagreements.

3.4. Data Collection Process

The data collection process consisted of using a data collection sheet, and collection was performed by one reviewer. Data were obtained by identifying each of the article's information in the common article information file and based on the full text of the articles. The data of the full-text articles were extracted on 10th December 2021. The data items on the data collection sheet consisted of the year of publication, name of the journal of the article, name of authors, name of title, the abstract, number of observations included in the analysis, unit of analysis, percentage of female participants, research design, controlled or field setting, dependent variable(s), independent variable(s), comparison of data method, effect strength, univariate or multivariate independent variables, findings of the study, type of FOP food labels, physical or digitalized FOP food label, and whether the FOP food labels were static, interactive or enabled by technology. The research designs were categorized into between-participant, within-participant, and non-experimental surveys. The dependent variables were categorized into purchase, consumption, hypothetical choices, and self-reports regarding healthy foods. Self-reports were defined as verbal estimations by participants measured by Likert-type scales. The type of FOP food label was categorized by single summary labels, graded summary labels, percentage-based nutrient-specific, single nutrient-specific labels, and graded nutrient-specific FOP food labels. The findings of the studies were summarized by describing the methods and results of each included study based on the participants, intervention, control condition, and outcome measurement. Physical FOP food labels were defined as labels being presented near the three-dimensional package of a product, digitalized static FOP food labels were defined as being a label presented on a picture of the product, digitalized interactive FOP food labels were defined with the same criteria as digitalized static FOP food labels but with the additional option to view more information of the label or food product, and digitalized FOP food technology-enabled labels were defined as labels that presented information which was personalized, dynamic, and real-time based on participants actions in the study.

3.5. Synthesis of Results

Six syntheses of results were used in this review. First, a methodological overview of each article was synthesized in a table by its article number and the first 11 data items (except item 2) specified in the data collection process. Second, FOP food labels used in included articles were synthesized in a table by article number, year of publication, author(s), whether the study used physical or digitalized FOP food labels, whether they were static, interactive or technology-enabled, and which type of FOP food label was used. Third, the findings of each article were synthesized in a table by article number, year of publication, author(s), and findings which were summarized by the method and results by describing the participants, intervention, control condition, and outcome variable (dependent variable) used in each article. Fourth, the number of articles that investigated physical and digitalized FOP food labels as a function of the year of publication is represented by a bar graph. Fifth, articles that investigated the effects of FOP food labels' presence compared to their absence on the dependent variable were synthesized by presenting how many articles investigated the physical, digitalized, digitalized static, digitalized interactively, and digitalized technology-enabled FOP food labels; and the percentage of articles that found that the dependent variables were under experimental control of these labels. Finally, articles that investigated the effects of FOP food labels' presence compared to their absence across the dependent variables were synthesized by presenting how many articles investigated the physical, digitalized, digitalized static, digitalized interactively, and digitalized technology-enabled FOP food labels, and whether purchase, consumption, hypothetical choice, or self-reports separately changed as a function of these labels.

3.6. Study Risk of Bias Assessment

This study used a risk of bias assessment based on the RoB 2 tool [46] for studies that used randomized controlled trials and an adapted Joanna Briggs Institute (JIB) checklist for non-randomized controlled studies [47] for all studies included in the review. For the randomized controlled trials studies, each study was assessed for bias due to the randomization process, deviation from intended intervention, missing data, measurement of outcomes, and reported results. An adherence assessment was used for deviations from intervention, and the additional risk of bias assessment was given for crossover and cluster randomized controlled trials. For the non-randomized controlled trials, each study was assessed for risk of bias regarding temporal relations between independent variables and their effects, participants' characteristics across groups, a clear procedure for each intervention, a control condition, multiple measurements of the outcome, missing data, measurement of outcome, and reliability of the outcome. Both the RoB 2 tool and adapted JIB Checklist were used to evaluate an overall risk of bias score, indicated by "Low risk", "Moderate risk", or "High risk" for each study. The original assessment for JIB was changed from "Yes", "No", or "Unclear" to the assessment mentioned above.

4. Results

4.1. Study Selection

A visual representation of the study selection process is shown in Figure 3. The search strategy resulted in the identification of 285 records. Fourteen of them were duplicates. They were removed. Two hundred and seventy-one were screened based on the first screening criteria, and 216 records were excluded for not meeting the criteria. All remaining 55 reports were sought for retrieval and assessed for eligibility. Out of those, a total of 25 reports were excluded based on the final eligibility criteria, as 10 of the reports did not investigate FOP food labels as defined in this review, five of the reports did not investigate behaviors related to healthy foods, four of the reports did not investigate the dependent variable specified in this review, and one report did not use primary data collection. This resulted in a total of 30 articles included in this review [15,33,48–75].

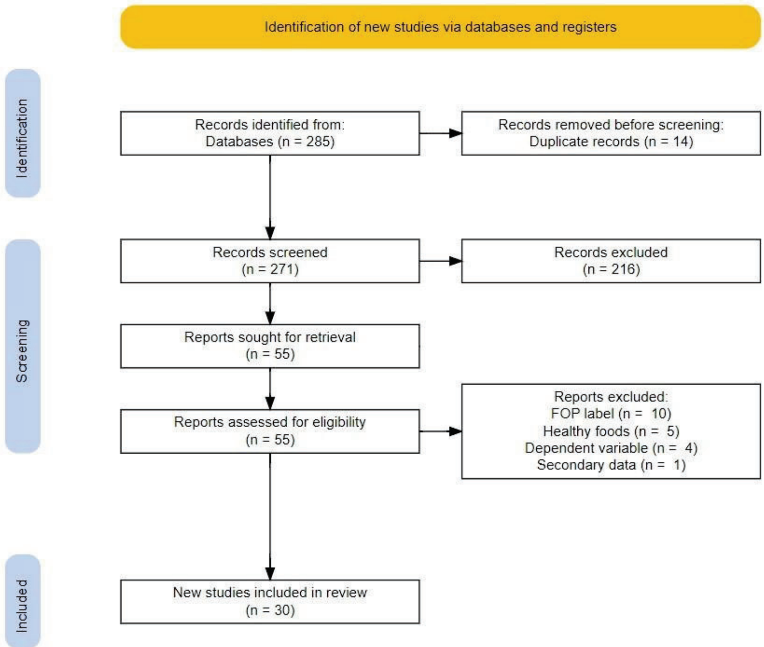

Figure 3. The flowchart shows the identification, screening, and inclusion of records, reports, and articles included on the left and reasons for removal on the right.

4.2. Study Characteristics

The methodological approach for each included article is shown in Appendix A Table A1. The most common units of analysis were participants. The studies had a variability range of 1902 regarding the participants, and approximately two-thirds of the studies had a female participant percentage between 30% and 60%. In regard to the research design of the articles, the majority were between-participant research design (52.9%), followed by within-participant research design (47.1%), and non-experimental surveys (0%). The majority of the studies were conducted in a controlled setting (76.7%). From most to least common approaches for measuring the dependent variable, the articles used self-report (46.7%), hypothetical choice (40%), purchase (11.1%), and consumption (2.2%). The independent variables that were investigated were different types of FOP food labels, labels with different product categories, nutritional information labels, different food products, textual health claims, brands, color-based labels, loss or gain framing, the time limit to shop, caloric information on each ingredient, caloric information relative to other ingredients, amount of labels within a food category, its correspondence to nutritional information, dynamic and real-time feedback, and preparation method for products. The three most common comparisons of data methods were ANOVA, t-tests, and chi-square tests, and the majority of the studies investigated multivariate independent variables.

The FOP food labels from each article are shown in Appendix A, in Table A2. Regarding physical and digitalized FOP food labels, seven articles investigated physical FOP food labels, and 23 articles investigated digitalized FOP food. Out of all included articles, 24 articles investigated static labels, six articles investigated interactively, and one article investigated technology-enabled FOP food labels. Regarding the type of FOP food labels, 24 out of 30 articles investigated nutrient-specific labels, while 12 out of 30 articles investigated summary labels. Specifically, 18 articles investigated graded nutrient-specific labels, 10 investigated single nutrient-specific labels, seven investigated graded summary labels, five investigated single summary labels, and five articles investigated percentage-based nutrient-specific labels.

The findings from each article are shown in Appendix A, in Table A3. Based on the findings of all 30 articles, 18 articles documented different values of the dependent variables in the presence of FOP food labels compared to the absence of such labels. Five articles found different effects of FOP food labels depending on which dependent variable was used. One article found no difference between the presence and absence of FOP food labels. The six remaining articles lacked an absence of label condition. In regard to all articles, 10 articles found differences between different types of FOP food labels, three articles found differences depending on which dependent variable was used, and 17 articles did not compare different types of FOP food labels as categorized by this review (e.g., some of the articles investigated several single nutrient-specific labels) or investigated only one label.

4.3. The Effects of Physical and Digitalized FOP Food Labels

The number of articles that have investigated either physical and digitalized FOP food labels and the year of publication is shown in Figure 4. The figure shows that the number of articles investigating digitalized FOP food labels increased steadily from 2011 to 2019 and that digitalized FOP food labels were higher in 2020 and 2021 than were physical FOP food labels.

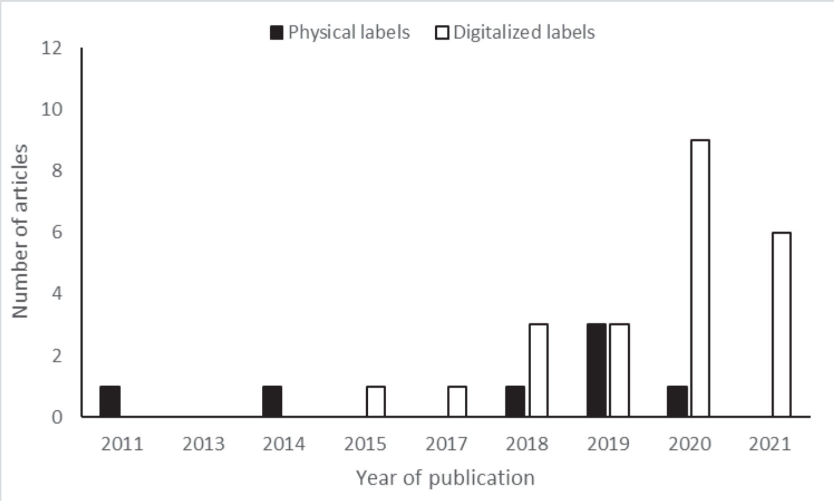

Figure 4. The *Y*-axis shows the number of articles included in this review, and the *X*-axis shows the year of publication for its corresponding article. The black bar corresponds to articles that investigated physical FOP food labels while the white bar corresponds to articles that investigated digitalized FOP food labels.

Articles that investigated the effects of the presence of physical and digitalized FOP food labels compared to their absence are shown in Appendix A, in Table A4. The effects of the presence of physical FOP food labels compared to their absence were investigated by six articles in this review. Out of those, five articles documented that the presence of physical FOP food labels was associated with a change in the dependent variables compared to the absence of FOP food labels. In contrast, the remaining articles had different results depending on the dependent variables being measured. The effects of the presence of digitalized static FOP food labels compared to their absence were investigated by 12 articles. Out of those, ten articles documented that the presence of digitalized static FOP food labels was associated with a change in the dependent variables. Two articles documented mixed results depending on which dependent variable was used. Five articles investigated the effects of digitalized interactive FOP food labels. Three of these documented a change in the dependent variable. One article found mixed results, and one article did not find differences. The effects of digitalized technology-enabled FOP food labels were investigated by one article, and it documented that the FOP food labels did change the dependent variables.

Articles in this review that investigated the effects of the presence of physical and digitalized FOP food labels compared to their absence across the dependent variables are shown in Table 1. In regard to purchasing as the dependent variable, one article did not find differences when exposed to physical FOP food labels, no articles examined digitalized static FOP food labels, two out of three articles found differences when exposed to digitalized interactive FOP food labels, and one article found differences when exposed to digitalized technology-enabled FOP food labels compared to the absence of such labels. Regarding consumption as the dependent variable, one article found differences when participants were exposed to physical FOP food labels compared to their absence, and no articles examined digitalized FOP food labels. Regarding hypothetical choice, two articles found differences when exposed to physical FOP food labels, all eight articles found differences when exposed to digitalized static FOP food labels, one out of two articles found differences when exposed to digitalized interactive FOP food labels, and no articles investigated the effects of digitalized technology-enabled FOP food labels. Regarding self-reports as the dependent variable, two out of three articles found differences when exposed to physical FOP food labels, three out of five articles found differences when exposed to digitalized static FOP food labels, no articles investigated the effects of digitalized interactive FOP food labels and digitalized technology-enabled FOP food labels.

Table 1. The effects of physical and digitalized FOP food labels across dependent variables.

Dependent Variable	Physical	Digitalized Static	Digitalized Interactive	Digitalized Technology-Enabled
Purchase	0% (10)		66.67% (1, 3, 20)	100% (25)
Consumption	100% (30)			
Hypothetical choice	100% (4, 11)	100% (6, 7, 11, 12, 15, 16, 28, 29)	50% (5, 14)	
Self-reports	33% (9, 10, 26)	60% (16, 17, 18, 22, 24)		

Note. The table shows the percentage of articles that indicate that the corresponding dependent variable was under full control of physical, digitalized static, digitalized interactive, and digitalized technology-enabled FOP food labels based on articles that had a presence and an absence of FOP food label conditions. Each article's number in the parentheses specifies the articles.

The most effective type of FOP food labels compared to other labels and their impact on purchase, consumption, hypothetical choice, and self-reports regarding healthy foods were also investigated. One article investigated multiple types of FOP food labels regarding physical FOP food labels and found that combined labels were most effective in changing the dependent variable. Specifically, Koeningstrofer et al. [51] investigated the effects of graded nutrient-specific, single summary, and combined FOP food labels on hypothetical choices and found that participants who were exposed to combined FOP food labels selected food products that had the least harmful nutrients based on the SSAg/1 scale [49]. Six articles investigated the effects of multiple types of FOP food labels regarding digitalized static FOP food labels. Three articles identified which type of FOP food label was most effective in changing the dependent variable, while the three remaining articles found inconclusive results. Two articles found graded nutrient-specific labels, and one found that graded summary labels were most effective. Specifically, Gustafson & Zeballos [62] investigated the effects of percentage nutrient-specific and graded nutrient-specific FOP food labels and found that graded nutrient-specific labels were most effective. Hagmann & Siergrist [63] investigated the effects of the graded nutrient-specific and summary labels and found that graded nutrient-specific labels were most effective. Gabor et al. [66] investigated the effects of graded nutrient-specific, graded summary labels, and percentage nutrient-specific labels and found that graded summary labels were the most effective. Deliza et al. [55] investigated percentage nutrient-specific labels, graded nutrient-specific labels, and single nutrient-specific labels, and Lima et al. [70] studied percentage nutrient-specific labels, graded nutrient-specific labels, and single nutrient-specific labels. Antunez et al. [60] investigated percentage nutrient-specific labels and graded nutrient-specific labels and did not find differences in effects as a function of the labels. Three articles investigated the effects of multiple FOP food labels on digitalized interactive FOP food labels. Two of those three articles found that graded summary labels were most effective in changing the dependent variable than other labels. The remaining article found that single nutrient-specific labels were most effective. Specifically, Finkelstein [48] investigated graded nutrient-specific labels and graded summary labels and found that graded summary labels were the most effective. Blitstein et al. [61] investigated graded summary labels, graded nutrient-specific labels, and combined labels and found that graded summary labels were most effective; and Finkelstein et al. [50] investigated single nutrient-specific labels and graded nutrient-specific labels and found that single nutrient-specific labels were most effective. Regarding digitalized technology-enabled FOP food labels, no article investigated the effects of different types of FOP food labels.

4.4. Risk of Bias in Articles

The risk of bias assessment for articles that used a between-participants design with randomization is shown in Appendix A, in Table A5. Out of all 22 articles, 12 articles were assessed as having a high overall risk of bias, nine articles were a moderate risk, and one article was low risk. Regarding the risk of bias domains, a high risk of bias was more common in the deviations from the intended intervention. A moderate risk of bias was more common in reporting of results. Low risk of bias was more common in the missing outcome data domain

The risk of bias assessment for studies that did not use a between-participant design with randomization is shown in Table A6. Six articles had a high overall risk of bias, and three articles had a moderate overall risk of bias. Regarding the risk of bias domain, both high and moderate risk of bias were more common in multiple measurements of outcome pre- and post-intervention domains. At the same time, nine articles had an overall low risk of bias regarding the temporal order of independent variable and effect, the procedure for interventions, measurement of outcome, and reliability of outcome domain.

5. Discussion

5.1. General Interpretation

This systematic review aimed to present a classification system and investigate the effects of physical and digitalized FOP food labels on healthy food-related behavior. Specifically, the articles that were collected investigated the effects of physical and digitalized static, interactive and technology-enabled FOP food labels on consumer purchases, consumption, hypothetical choices, and self-reports regarding healthy foods. To the best of the authors' knowledge, this study is the first study to do so.

The results show a difference in the dependent variables defined in this review as a function of digitalized FOP food labels when analyzed individually. Based on the articles included in this review, a higher percentage of articles found a difference in purchase and self-reports regarding digitalized FOP food labels compared to the percentage of articles that used physical FOP food labels. A similar percentage of articles found a difference in hypothetical choices regarding digitalized FOP food labels compared to articles that investigated physical FOP. No articles investigated consumption as a function of digitalized FOP food labels. Hence, the results indicate that the effects of digitalized FOP food labels are greater for purchase and self-reports compared to physical FOP food labels. Furthermore, in the context of digitalized static FOP food labels, more articles reported a change of hypothetical choice compared to articles that investigated self-reports.

When analyzed collectively, the results show a difference in the dependent variables defined in this review as a function of digitalized FOP food labels. The results show that the percentage of articles that found differences between the dependent variables was the same when articles investigated physical and digitalized static FOP food labels. The results also show that the percentage of articles that found a difference between the dependent variables was lower as a function of digitalized interactive FOP food labels than physical FOP food labels. In addition, a higher percentage of articles found a difference in the dependent variable as a function of digitalized technology-enabled FOP food labels compared to physical FOP food labels. Hence, the percentage of articles that found an effect was similar for digitalized static, lower for digitalized interactive, and higher for digitalized technology-enabled FOP food labels than physical FOP food labels when the dependent variables were analyzed collectively. However, more studies are needed to evaluate the effects of digitalized FOP food labels.

Lastly, when compared to different types of FOP food labels and their effectiveness in changing healthy food-related behaviors, combined labels were documented as the most effective for physical, graded nutrient-specific for digitalized static, graded summary labels for digitalized interactive FOP, and no articles investigated the effects digitalized technology-enabled FOP food labels. However, these articles did not compare the same type of FOP food label. Further research is needed to identify which type of FOP food labels are more effective when presented as physical, digitalized static, digitalized interactive, and digitalized technology-enabled FOP food labels.

The articles identified in the introduction and articles which were included in the review had different results in regard to physical labels, to some degree similar results in regard to digitalized static, non-consistent results in relation to digitalized interactive, and was the same article in regard to digitalized technology-enabled FOP food labels. The results of the articles in this review do not align with the results in the literature review. Specifically, one article did not find the difference in purchase [57], one article did find a difference in consumption [75], two articles found a difference in hypothetical choice [51,58], and one did find differences in self-reports article [56] while two articles did not find a difference in self-reports [33,57] as a function of physical FOP food labels. In contrast to previous research, one article did find differences in purchases when self-reports regarding self-control were high [34], one article did not find a difference in hypothetical choice [35], and all three articles found differences in self-reports as a function of physical FOP food labels [19,34,35]. Digitalized static FOP food labels and their effects on healthy food-related behavior based on the articles included in this review are, to some degree, in line with the results of prior research identified in the literature review section. In our systematic review, eight articles did find differences in hypothetical choices [52–54,58,59,62,63,73,74], three articles did find difference in self-reports [63,65,71], while two articles did not find difference in self-reports [64,69] as a function of digitalized static FOP food labels. Based on the studies that were identified in the literature review, two articles did find differences in hypothetical choice [17,37], and two articles did find differences in self-reports [36,37] as a function of digitalized static FOP food labels. The effects of digitalized interactive FOP food labels on healthy food-related behavior, based on the articles included in this review, are non-consistent with effects identified prior research mentioned in the literature review section. In our review, two articles found differences in purchases [48,50] while one article did not find differences [67], one article found differences in hypothetical choice [61] while one article did not find differences [52]. Regarding research in the literature review, one article did not find the difference [41] while one article found an increase in purchase [42], two articles found a difference in hypothetical choice [38,39], and one article found a difference in self-reports [40] as a function of digitalized interactive FOP food labels. The effects of digitalized technology-enabled FOP food labels and their effects on healthy food-related behavior were the same as in articles identified in this review and previous research [15] indicating a lack of research regarding digitalized technology-enabled FOP food labels, as shown in Table 1.

There are several alternative explanations regarding the general interpretation of this review. Firstly, this systematic review found different results when healthy food-related behavior was analyzed collectively or individually. When healthy food-related behaviors were analyzed collectively, then similar percentages of articles that found differences in the dependent variable as a function of physical and digitalized static FOP food labels were found. However, when the percentage of articles was analyzed across the dependent variables, a higher percentage of articles were found that documented a change in self-reports as a function of digitalized static FOP food labels compared to physical FOP food labels. One possible explanation is that the search strategy that was used found more articles that investigated the effects of digitalized static FOP food labels on hypothetical choices. The results may have been different if the search strategy identified an equal number of articles that investigated the effects of physical, digitalized static, digitalized interactive, and digitalized technology-enabled FOP food labels on purchase, consumption, hypothetical choice, and self-report. In addition, hypothetical choices regarding preference often involve repeated evaluations by the participants while self-reports may require a single evaluation. This may have impacted the results. Secondly, more articles support that physical and digitalized FOP food labels change hypothetical choices than do articles that used self-reports as the dependent variable. One possibility is that it may be more practical to measure several self-report measurements, such as ratings of healthfulness, taste, affect, and so on, through a questionnaire that presents several such questions compared to measuring several hypothetical choices. The increase in measurements with self-report may increase the probability of not finding changes.

These findings imply that physical and digitalized labels may have different impacts on consumer behavior and there may be several possible mechanisms for these findings. First, it may be the case that the actual sight and symbolic representation of food products may have different impacts on healthy food-related behavior. For instance, Huyghe and collages [76] conducted a series of experiments regarding online and offline grocery shopping on healthy food-related behaviors. Their results indicate that symbolic representation of a product may impact self-control and that may impact healthy food purchases [34]. Furthermore, online grocery stores provide the possibility of presenting pre-selected food products along with recipes (meal kits). The effects of digitalized FOP food labels may function differently when they are based on a collection of many products compared to individual products. Finally, consumers can use a variety of sensory modalities to assess a food product before purchasing it in a physical store whereas online grocery stores provide no specific sensory information such as smell and touch. In an online grocery store, one can present textual descriptions of sensory information based on the association between previously purchased products; for instance, a message at the point of purchase that suggests that a particular brand of apple has the same "taste profile" as other previously purchased products. The presence or absence of these variables may influence the effectiveness of certain digitalized FOP food labels.

5.2. Limitation of Evidence Based on Articles and Review

There exist several limitations of evidence based on the articles. Firstly, the majority of the articles included in this review had an overall moderate or high risk of bias. Specifically, reporting of results was the risk of bias domain that had the least "Low risk" assessments. The majority of these articles had a moderate risk of bias, where there was no provided information on a pre-specified statistical analysis plan. Secondly, the majority of the articles investigated the effects of digitalized static FOP food on hypothetical choices or self-reports. There is a lack of articles examining the effects of digitalized static FOP food labels effects on purchase and consumption, the effects of digitalized interactive FOP food labels on consumption and self-reports, and the effects of digitalized technology-enabled FOP food labels in general, except for one article.

Several methodological limitations of this review are also worth addressing. Firstly, the search strategy may have been too restrictive regarding identifying all articles investigating the effects of physical and digitalized FOP food labels. However, this systematic review aimed to investigate the effects of physical and digitalized FOP food labels on healthy food-related behavior and not to identify all previous research that has examined FOP food labels. Furthermore, this systematic review used only principal search systems which do not include Google Scholar. This may have impacted the number of articles that have investigated the effects of digitalized static FOP food labels included in the review. However, the number of articles that investigated interactive and technology-enabled FOP food labels produced by search engines is not likely to be affected. Secondly, one reviewer did the risk of bias assessment and the data collection process, apart from the findings of articles that another independent reviewer assessed. Thirdly, tools regarding the certainty of assessment were not used. However, issues regarding the articles identified were discussed in regard to limitations of evidence based on the studies. Several articles included in this review had an overall moderate to high risk of bias. Hence, presenting a meta-analysis that investigated the degree of effects was not appropriate. Furthermore, several articles used different measurements concerning the dependent variable. For instance, one article could present three food products, and another could present six food products when measuring hypothetical choices regarding healthy food. A meta-analysis would be appropriate if the articles in this review used the same experimental paradigm. However, a meta-analysis was not done due to a large variation in experimental designs.

This review instead investigated how many empirical articles found a difference in healthy food-related behavior as a function of physical and digitalized FOP food labels instead of directly comparing different dependent variables. Lastly, this review did not control for the confounding effects of nutritional fact labels. Future studies could address this and examine the confounding effects of nutritional information labels and digitalized FOP food labels. To control for the confounding effects would require a larger sample of empirical studies that met the inclusion parameters of this study. However, in this study, it was not feasible to perform such an analysis. Future studies could address this and examine the confounding effects of nutritional fact format and digital labeling format.

5.3. Implications and Further Research

Several implications exist based on the findings of this review. Firstly, this review found an increase in research articles regarding digitalized FOP food labels. This trend indicates that investigations into the effects of such labels are increasing and will be important for future online grocery retailing practices. Secondly, this review found one article [15] which investigated the effects of digitalized technology-enabled FOP food labels and found a reliable increase in healthy food purchases and a decrease in unhealthy nutrients while at the same time not showing significant differences in dollars spent per kcal, indicating that one indeed can increase healthy food purchase without decreasing profit. As mentioned, digitalized technology-enabled FOP food labels may increase the number of healthy food purchases, attract new customers, and increase the positive reputation of online grocery stores and brand owners such as Thrive Market, Tesco, Sainsbury, Walmart, and AmazonFresh. Even though digitalized interactive FOP food labels alone may not change purchases, such labels may still provide consumers with accurate descriptions of food products. They may attract new consumers and increase positive word of mouth regarding brand owners and retailers.

One way to advance further studies regarding digitalized technology-enabled FOP food labels is to conduct controlled laboratory experiments regarding how previous neutral symbols or stimuli may acquire a function as a healthy food label in individual analysis. As mentioned, the effects of such labels may increase the purchase of healthy foods for some subgroups [5]. Previous history with interactions with these labels may be one variable that may impact their effectiveness. The majority of the articles studied healthy food labels implemented through public policy. Participants presumably had some history regarding such labels and this may influence the effectiveness of such labels in changing healthy food-related behavior. Although further studies regarding how different FOP food labels impact different subgroups are needed [7], there is also a need to identify how the presentation of information or stimuli, in general, may impact healthy food-related behavior on an individual psychological and behavioral level, and then replicate such findings on a large scale level. Future studies regarding digitalized technology-enabled FOP food labels could, in combination, investigate the effects of automatic self-monitoring of healthy food purchases, presentation of healthy food labels on food products that have not been purchased previously in order to increase variability regarding food choices, decreasing the delay of future consequences by presenting real-time based health-related information such as a decreasing in the chance of illnesses associated with healthy food purchases, self-imposed costs or restriction of unhealthy foods in the combination of single nutrient-specific labels, other consumers FOP food label scores, and immediate or delayed presentations of such labels (e.g., real-time based versus every third purchase based on products in virtual basket). One way to advance further studies regarding digitalized interactive FOP food labels is to examine their effects on hypothetical choice, self-reports, and food consumption. As mentioned, articles that have used self-reports as the dependent variables may have measured various constructs such as healthfulness, trust, familiarity, etc., compared to hypothetical choice. Further studies could investigate such constructs.

6. Conclusions

In conclusion, digitalized interactive and technology-enabled FOP food labels and their effects on healthy food-related behavior remain an unexplored research area. This systematic review identified previous research regarding physical, digitalized static, digitalized interactive, and digitalized technology-enabled FOP food labels and investigated their effects on healthy food-related behavior regarding purchase, consumption, hypothetical choice, and self-reports. When analyzed collectively, a similar percentage of articles demonstrated the effects of physical and digitalized static FOP food labels on healthy food-related behavior. Furthermore, a lower percentage of articles demonstrated the effects of digitalized interactive FOP food labels compared to physical FOP food labels. However, a higher percentage of articles demonstrated the effects of digitalized technology-enabled FOP food labels. When analyzed individually, a higher percentage of articles supported a difference in purchase and self-reports as a function of physical and digitalized FOP food labels. Regarding articles identified in this review that compared different types of FOP food labels, including physical combined, digitalized static graded-nutrient, and digitalized interactive graded summary, FOP food labels were most effective. Our results show that there is an increase in the publication of studies regarding digitalized FOP food labels and their effect on healthy food-related behavior. Knowledge regarding variables that moderate these effects would be important for future studies.

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Appendix A

Table A1. Methodology of the included articles.

Article	Year of Publication	Author(s)	Number of Observations	Unit of Analysis	Percentage Female Participants	Research Design	Controlled or Field Setting	Dependent Variable(s)	Independent Variable(s)	Comparison of Data Method	Univariate or Multivariate Independent Variable(s)
1	2019	Finkelstein et al. [48]	147	Participants	68.8%	Within-participant design	Field setting	Purchase	Multiple traffic light label, Nutri-score label	First difference model	Multivariate independent variables
2	2019	Reyes et al. [49]	Study 1: 600 Study 2: 700	Participants	100%	Within-participant design	Controlled setting	Hypothetical choice, self-report	15 warning labels	Study 1: ANOVA, Bonferroni Study 2: Chi-square, t-test	Multivariate independent variables
3	2020	Finkelstein et al. [50]	146	Participants	78.8%	Within-participant design	Field setting	Purchase, self-report	"Lower calorie" labeling on within-category products, "Lower calorie" labeling on across category products	First difference approach	Multivariate independent variables
4	2014	Koenigstorfer et al. [51]	152	Participants	63.5%	Between-participant design	Controlled setting	Hypothetical choice	Health mark label, traffic lights color-coding label	Two-factorial ANOVA	Multivariate independent variables
5	2019	Siegrist et al. [52]	780	Participants	51.5%	Between-participant design	Controlled setting	Hypothetical choice	Healthy choice label, nutritional information label	Kruskal–Wallis test, Mann–Whitney U test	Multivariate independent variables
6	2021	Miklavec et al. [53]	1000	Participants	49%	Within-participant design, between-participant design	Controlled setting	Self-report, hypothetical choice	Type of product, brand name with labels, health claim	Not specified for conjoint analysis, t-test	Multivariate independent variables
7	2020	Alcantara et al. [54]	1232	Participants	52%	Between-participant design	Controlled setting	Hypothetical choice	Health logo, nutritional warning label	Generalized linear model, Tukey's test	Multivariate independent variables
8	2020	Deliza et al. [55]	Study 2: 1932	Participants	51%	Between-participant design	Controlled setting	Hypothetical choice, self-report	Guideline daily amount, traffic light system, black magnifier, red magnifier, red circle, black triangle, and black octagon label	ANOVA, generalized linear model, t-test	Multivariate independent variables
9	2019	Lima et al. [56]	141	Participants	60%	Within-participant design	Controlled setting	Self-report	Types of dairy products, traffic light system, familiar brands	ANOVA, Tukey's test, exploratory factor analysis, parallel analysis, maximum likelihood estimation, pro max	Multivariate independent variables
10	2011	Vyth et al. [57]	Study 1: 25 Study 2: 368	Study 1: Cafeterias Study 2: Participants	Not collected	Within-participant design, between-participant design	Field setting	Purchase, self-report	Choices logo on sandwiches, choices logo on soups, sandwiches, and soups	Generalized estimation equation analysis, t-test	Multivariate independent variables

Table A1. *Cont.*

Article	Year of Publication	Author(s)	Number of Observations	Unit of Analysis	Percentage Female Participants	Research Design	Controlled or Field Setting	Dependent Variable(s)	Independent Variable(s)	Comparison of Data Method	Univariate or Multivariate Independent Variable(s)
11	2019	Machin et al. [58]	199	Participants	66%	Between-participant design	Controlled setting	Self-report, hypothetical choice	Calorie, added sugar, total fat, saturated fat, and sodium-based warning labels	Chi-square test, *t*-test	Multivariate independent variables
12	2018	Kim et al. [59]	95	Participants	54.7%	Within-participant design	Controlled setting	Hypothetical choice	Numeric, color-coded, and physical activity-based labels	Chi-square test, one-way ANOVA, Tukey test	Multivariate independent variables
13	2015	Antunez et al. [60]	54	Participants	53%	Within-participant design	Controlled setting	Hypothetical choice	Color without text, color with text, monochromatic without text, monochromatic with text	ANOVA	Multivariate independent variables
14	2020	Blitstein et al. [61]	1452	Participants	83.5%	Between-participant design, within-participant design	Controlled setting	Hypothetical choice, self-report	Summary label, nutrient-specific label, hybrid label, 10-min time limit to shop	Tukey–Kramer adjustment, ANCOVA,	Multivariate independent variables
15	2020	Gustafson & Zeballos [62]	633	Participants	53%	Between-participant design	Controlled setting	Hypothetical choice	Calorie information for each ingredient, calorie information relative to highest calorie item, calorie information relative to lowest calorie item	T-test, linear regression analysis, chi-square tests, Bonferroni Correction	Multivariate independent variables
16	2020	Hagmann & Siegrist [63]	1313	Participants	53.9%	Between-participant design	Controlled setting	Hypothetical choice, self-report	Nutritional information label, multiple traffic light, Nutri-score, Nutri-score on half of the products	Welch's analysis of variance (ANOVA), Games-Howell post hoc test, Kruskal–Wallis test, Pearson's r, one-way ANOVA, exploratory t-tests independent samples	Multivariate independent variables
17	2018	Menger-Ogle & Graham [64]	239	Participants	59%	Within-participant design	Field setting	Self-report	"Low fat", "> 100% RDA of vitamin C", "35% RDA of vitamin A", "Low fat, low sugar, transfat free", "zero cholesterol, zero trans fat, gluten-free, MSG-free" labels	Mediational model, t-test,	Multivariate independent variables
18	2019	Vizcaino & Velasco [65]	Study 1: 133 Study 2: 837 Study 3: 181 Study 4: 201	Participants	Study 1: 38%Study 2: 53%Study 3: 46.7% Study 4: 71.1%	Between-participant design	Controlled setting	Self-report	Traffic light labels, brand familiarity	ANOVA, mediation analysis, multiple moderation regression, moderated-mediation analysis	Multivariate independent variables
19	2020	Gabor et al. [66]	76	Participants	55%	Between-participant design	Controlled setting	Self-report	Nutri-score, multiple traffic lights, guideline daily amount	ANOVA, Tukey's test	Multivariate independent variables

Table A1. *Cont.*

Article	Year of Publication	Author(s)	Number of Observations	Unit of Analysis	Percentage Female Participants	Research Design	Controlled or Field Setting	Dependent Variable(s)	Independent Variable(s)	Comparison of Data Method	Univariate or Multivariate Independent Variable(s)
20	2021	Finkelstein et al. [67]	106	Participants	66%	Within-participant design	Field setting	Purchase	Healthier choice, physical activity equivalent, and nutritional information label	First-differenced regressions	Multivariate independent variables
21	2021	Fagerstrøm et al. [68]	30	Participants	46.7%	Within-participant design	Controlled setting	Hypothetical choice	Correspondence of healthy food labels and nutritional information	Share of correct choice	Univariate independent variable
22	2021	Folkvord et al. [69]	192	Participants	63%	Between-participant design	Controlled setting	Self-report	Nutri-score	Chi-square test, MANOVA, Bayesian ANCOVA	Univariate independent variable
23	2018	Lima et al. [70]	Sample 1: 318 Sample 2: 278	Participants	Sample 1: 83% Sample 2: 49%	Between-participant design	Controlled setting	Self-report	Daily guideline amounts, traffic light systems, and warning systems	ANOVA, Tukey's test	Multivariate independent variables
24	2017	Yoo et al. [71]	646	Participants	56%	Within-participant design	Controlled setting	Self-report	Dairy product, sugar reduction claim, traffic light system	ANOVA, generalized linear model	Multivariate independent variables
25	2020	Shin et al. [15]	125	Participants	72%	Between-participant design	Field setting	Purchase, self-report	Nutri-score, physical activity equivalents, calorie, sugar, sodium, saturated fat, and total fat per serving and percentage daily recommended intake dynamic with real-time feedback labels	First difference regression	Multivariate independent variables
26	2018	Acton et al. [33]	675	Participants	53.9%	Between-participant design	Field setting	Self-report	Numeric rating, health star rating, traffic light symbol	Chi-square test, logistic regression model	Multivariate independent variables
27	2020	Rojas-Rivas et al. [72]	498	Participants	73%	Within-participant design	Controlled setting	Self-report	Sodium warning, type of bread, brand, price	Exploratory factor analyses, maximum likelihood and Promax rotation method, mixed logit model	Multivariate independent variables
28	2021	Yang et al. [73]	1215	Participants	62.2%	Within-participant design	Controlled setting	Hypothetical choice, self-report	Health label, low-carbon label, the proportion of brown rice, pre-treatment, price	Mixed logit model,	Multivariate independent variables
29	2021	Mauri et al. [74]	Study 1: 200 Study 2: 272	Participants	Study 1: 66.8% Study 2: 71.7%	Between-participant design	Controlled setting	Hypothetical choice, self-report	Sugar teaspoons, traffic lights,	ANOVA, Mediation testing	Multivariate independent variables
30	2020	Jin et al. [75]	Study 1: 123 Study 2: 144 Study 3: 241	Participants	Study 1: 51.2% Study 2: 49.3% Study 3: 46.9%	Between-participant design	Controlled setting	Self-report, consumption	Physical activity equivalent to calorie label	Moderated regression analysis	Multivariate independent variables

Note. Each included article is shown vertically while the methodological approach used by each article is presented horizontally.

Table A2. Front of package food labels used in included articles.

Article	Year of Publication	Author(s)	Physical or Digitalized FOP Food Label	Static, Interactive, or Technology-Enabled	Type of FOP Food Label
1	2019	Finkelstein et al. [48]	Digitalized	Interactive	Graded nutrient-specific label, graded summary label
2	2019	Reyes et al. [49]	Physical		Singe nutrient-specific label
3	2020	Finkelstein et al. [50]	Digitalized	Interactive	Singe nutrient-specific label
4	2014	Koenigstorfer et al. [51]	Physical		Graded nutrient-specific label, single summary label, combined label
5	2019	Siegrist et al. [52]	Digitalized	Interactive	Single summary label
6	2021	Miklavec et al. [53]	Digitalized	Static	Graded nutrient-specific label
7	2020	Alcantara et al. [54]	Digitalized	Static	Single nutrient-specific label
8	2020	Deliza et al. [55]	Digitalized	Static	Percentage nutrient-specific label, graded nutrient-specific label, single nutrient-specific labels
9	2019	Lima et al. [56]	Physical		Graded nutrient-specific label
10	2011	Vyth et al. [57]	Physical		Single summary label
11	2019	Machin et al. [58]	Physical		Single nutrient-specific label
12	2018	Kim et al. [59]	Digitalized	Static	Graded nutrient-specific label
13	2015	Antunez et al. [60]	Digitalized	Static	Percentage nutrient-specific label, graded nutrient-specific label
14	2020	Blitstein et al. [61]	Digitalized	Interactive	Graded summary label, graded nutrient-specific label, combined label
15	2020	Gustafson & Zeballos [62]	Digitalized	Static	Graded nutrient-specific label, percentage nutrient-specific label
16	2020	Hagmann & Siegrist [63]	Digitalized	Static	Graded nutrient-specific label, graded summary label
17	2018	Menger-Ogle & Graham [64]	Digitalized	Static	Single nutrient-specific label
18	2019	Vizcaino & Velasco [65]	Digitalized	Static	Graded nutrient-specific label, single nutrient-specific label

Table A2. *Cont.*

Article	Year of Publication	Author(s)	Physical or Digitalized FOP Food Label	Static, Interactive, or Technology-Enabled	Type of FOP Food Label
19	2020	Gabor et al. [66]	Digitalized	Static	Graded nutrient-specific label, graded summary label, percentage nutrient-specific label
20	2021	Finkelstein et al. [67]	Digitalized	Interactive	Single nutrient-specific label, graded nutrient-specific label
21	2021	Fagerstrøm et al. [68]	Digitalized	Static	Single summary label
22	2021	Folkvord et al. [69]	Digitalized	Static	Graded summary label
23	2018	Lima et al. [70]	Digitalized	Static	Percentage nutrient-specific label, graded nutrient-specific label, single nutrient-specific labels
24	2017	Yoo et al. [71]	Digitalized	Static	Graded nutrient-specific label
25	2020	Shin et al. [15]	Digitalized	Technology-enabled	Graded summary label, graded nutrient-specific label
26	2018	Acton et al. [33]	Physical		Graded summary label
27	2020	Rojas-Rivas et al. [72]	Digitalized	Static	Single nutrient-specific label
28	2021	Yang et al. [73]	Digitalized	Static	Single summary label
29	2021	Mauri et al. [74]	Digitalized	Static	Graded nutrient-specific label
30	2020	Jin et al. [75]	Physical		Graded nutrient-specific label

Note. Each included article is shown vertically while information regarding the front of package labels used is presented in the last row.

Table A3. Findings from included articles.

Article	Year of Publication	Author(s)	Findings
1	2019	Finkelstein et al. [48]	Consumers shopped at online grocery stores and were exposed to (a) Multiple traffic light labels, (b) Nutri-score labels, or (c) no FOP food labels conditions. The results show that both labels increased the purchase of healthy products with no difference between labels. In contrast, the Nutri-score label increased average Nutri-score selection higher than multiple traffic light labels and no label.
2	2019	Reyes et al. [49]	Study 1: Participants were instructed to select between 2 out of 15 yogurts with different warning labels and asked to rate visibility, understanding, intend purchase score, ability to modify intend to purchase, and socio-demographical information. The results show that five distinct labels were associated with greater visualization, intended purchase score, and ability to modify intended purchase. Study 2: New participants were instructed to select one out of two warning labels which were based on the five warning labels in a previous study, and used the same measurement as the previous study. The results show that the stop sign label was associated with a greater effect on all ratings.
3	2020	Finkelstein et al. [50]	Consumers shopped at online grocery stores and were exposed to (a) "Lower calorie" label on 20% of foods within a product category, (b) "Lower calorie" label on 20% of all foods, or (c) no FOP food labels conditions. The results show that within-category labeling increased purchase of labeled foods compared to no label, no differences in within- and across- category labeling, and no evidence of a decrease in calories purchased in the latter.
4	2014	Koenigstorfer et al. [51]	Participants were randomly assigned to either (a) health mark and traffic light labels present, (b) health mark present and traffic light absent, (c) health mark absent and traffic light present, and (d) no labels. The results show that participants exposed to both labels selected healthier foods compared to other conditions.
5	2019	Siegrist et al. [52]	Participants were randomly assigned to (a) combined healthy choice and nutritional information label, (b) healthy choice label, (c) nutritional information label, and (d) no label condition; they were presented pairs of food and instructed to select the healthiest product. Healthy choice labels were presented on healthier options and nutritional information labels on both options. The results show that the nutritional information label slightly improved healthy choices, combined labels produced similar results, and that healthy choice labels alone and no label produced similar results.
6	2021	Miklavec et al. [53]	Participants were presented with fictive products with different combinations of types of products (soft drink, yogurt, and chocolate), brand name (three neutral circles, one heart, or three hearts), and claim (no claim, general claim, specific claim), and asked to rate how healthy the product was. Later, participants were assigned in (a) a heart symbol label condition and (b) no heart symbol label condition, presented for four existing brands of water bottles where one of the products in the former condition had a heart symbol, and instructed to rate how healthy the product was compared to tap water. The results show that the type of product, claims, and brand name had the highest impact in that order, and that the water bottle with heart symbols had the highest impact on the rating.

Table A3. *Cont.*

Article	Year of Publication	Author(s)	Findings
7	2020	Alcantara et al. [54]	Participants were allocated to either (a) health logo condition, (b) nutritional warning condition, and (c) no label condition, presented with three products each from a different category, and instructed to select which one they would like to buy. The results show that nutritional warnings were more effective than health logos in increasing product selection in all product categories, although both increased product selection compared to the no-label condition.
8	2020	Deliza et al. [55]	Participants were allocated to either (a) guideline daily amount, (b) traffic-light system, (c) black magnifier, (d) red magnifier, (e) red circle, (f) black triangle, and (g) black octagon label condition, and were presented with three products each having a different label and product category. Half of the participants were instructed to select the healthy product while the other half selected the unhealthy product. Later, participants were instructed to rate how healthy the product was. The results show that traffic-light, red circle, black triangle, black octagon, black magnifier, and guideline daily amount labels from, most to least in that order, were associated with healthier responses. Guideline daily amounts were associated with higher ratings of healthfulness than warning labels.
9	2019	Lima et al. [56]	Participants were presented with food products with different combinations of dairy products (yogurt, cheese, and chocolate-flavored milk), traffic light system (yes vs. no), and brand (well-known vs. unknown), were presented one product at a time, and instructed to rate how healthy the product was. The result shows the relative impact on ratings, from most to least, were the type of dairy product, traffic light system, and brand. The yogurt with the traffic light system and a familiar brand was on average, rated as healthier.
10	2011	Vyth et al. [57]	Consumers in 25 different cafeterias were exposed for cycles of nine weeks of (a) baseline condition with no Choices logo, (b) Choices logo on sandwiches, soups, and fresh fruits, and (c) postintervention period without the label, each condition lasting three weeks. Cycles were repeated three times. Consumers' purchases and employees near the cafeterias self-reports regarding attitudes, self-efficacy, intention, and whether they used the logo, were measured. The intervention did not significantly affect employees' lunchtime food choices. However, the results show that fruits sales were higher in the logo condition compared to its absence, while purchases of sandwiches and soups were similar across the conditions.
11	2019	Machin et al. [58]	Participants were allocated to (a) warning label condition or (b) no label condition; they were exposed to 15 snack products based on six food categories (fruit, alfajor, cereal bar, cracker, cookies, and peanuts; and were instructed to select a snack they would like to consume. The results show that participants allocated to the warning label condition selected fewer products that were excessive in at least one nutrient than participants in the no label condition.
12	2018	Kim et al. [59]	Participants were allocated to (a) color-coded calorie label condition, (b) physical activity-based condition, or (c) numeric calorie label condition; they were instructed to choose one burger/sandwich, snack/sides, and beverage; each category had six options. The results show that participants being exposed to the physical activity-based label, color-coded label, and numeric label led from most to least, to fewer calories selected.

Table A3. *Cont.*

Article	Year of Publication	Author(s)	Findings
13	2015	Antunez et al. [60]	Participants were exposed to a series of three products with a combination of the type of label (color or no color; text or no text) and a number of excess nutrients (all medium; one excessive nutrient content) and were asked to indicate which of three labels were low-fat and classify which product had lowest salt content. The results show that the percentage of correct responses was higher during color-coded than monochromatic labels for low-fat ratings but not for low salt ratings.
14	2020	Blitstein et al. [61]	Participants were allocated to (a) summary label condition, (b) nutrient-specific label condition, (c) hybrid label condition, or (d) no label condition; participants had either a time constraint of 10 min for shopping or were without such time constraints; and were instructed to select the six healthiest products for their family. The results show that the participants exposed to summary or hybrid labels made healthier choices than those exposed to nutrient-specific labels. The time constraint led to less healthier choices than no time constraint for participants exposed to summary or hybrid labels but not for nutrient-specific labels.
15	2020	Gustafson & Zeballos [62]	Participants were allocated to (a) calorie information condition, (b) calorie information relative to highest calorie item, (c) calorie information relative to lowest calorie item, and (d) no label condition; they were instructed to select which items they would like for constructing a fictive sandwich. The results show that participants exposed to relative calorie labels had fewer selected calories than those with no label. There were no significant differences between the calorie label and no label condition.
16	2020	Hagmann & Siegrist [63]	Participants were allocated to (a) nutritional information condition, (b) multiple traffic light condition, (c) Nutri-score condition, (d) Nutri-score on half of products condition, and (e) no label condition; they were presented with two products and instructed to select the healthiest option. The results show that the proportion of correct choices was higher for participants exposed to the Nutri-score label than respondents in other conditions.
17	2018	Menger-Ogle & Graham [64]	Participants were exposed to two of four possible food products with labels, instructed to rate how likely they were to purchase the product, the influence of such messages on their own purchase behavior, the healthfulness of the product, and the truthfulness of the message being presented. The results based on mediation models show that labels such as "healthful for children" influenced product perceptions while labels like "tasty" influenced purchase intention.
18	2019	Vizcaino & Velasco [65]	Study 1: Participants were allocated in either (a) traffic light condition or (b) no label condition, were presented a yogurt, and asked to rate how likely they were to purchase. Study 2: Participants were allocated in either (a) familiar brand and traffic light label, (b) unfamiliar brand and label, (c) familiar brand and no label, and (d) unfamiliar brand and no label, and were instructed to rate the trustworthiness of the product. Study 3: Used the same procedure as the second study but used different food categories.Study 4: Used the same procedure as study 2, used different foods and performed a moderation-mediation model.The results of these studies show a higher degree of purchase ratings when exposed to traffic lights, that familiar brands with traffic lights did produce interaction effects, and that brand trust may mediate the interaction of traffic lights and brand familiarity.

Table A3. *Cont.*

Article	Year of Publication	Author(s)	Findings
19	2020	Gabor et al. [66]	Participants were allocated to (a) multiple traffic light conditions, (b) Nutri-score condition, and (c) guideline daily amounts label condition; presented food products, instructed to rate how healthy the product is and how often they consumed such products. The results show that Nutri-score, multiple traffic lights, and guideline daily amounts condition produced high to low ratings of healthfulness and consumption frequency in that order.
20	2021	Finkelstein et al. [67]	Consumers shopped at an online grocery store and were exposed to (a) healthier choice label condition, (b) healthier choice and physical activity equivalent labels condition, and (c) no label condition; while their purchases were recorded and used to derive total calories, Grocery Purchase Quality Index 2016, weighted average Nutri-scores, sugar, sodium, saturated fat, and calories per dollar spent. The results show that healthier choices increased purchases of labeled products. In contrast, healthier choice labels combined with physical activity equivalents did not lead to a greater increase in healthy food purchases.
21	2021	Fagerstrøm et al. [68]	Participants were exposed to (a) correspondence between healthy food labels and nutritional information labels, (b) non-correspondence between healthy food labels, (c) healthy food labels on both products, and (d) no label conditions; presented with two food products with their respective nutritional information, and instructed to select the healthier product. The results show that approximately two-thirds of the participants chose the healthier option when there was a correspondence. Approximately one-third of participants continued to select the healthier option when there was non-correspondence.
22	2021	Folkvord et al. [69]	Participants were allocated in either (a) Nutri-score condition or (b) no label condition; they were instructed to rate how appealing the product looked, how tasty the product looked, and how likely they were to purchase the product. The results show that the participants' ratings of appeal, ratings of tastiness, and purchase intention did not differ between the groups.
23	2018	Lima et al. [70]	Participants (parents and children) were allocated to (a) guideline daily amounts, (b) traffic light systems, or (c) warning system conditions; and instructed to rate how healthy the product was and how often they consume such products. The results show that ratings of healthfulness were lower for participants in the traffic light and warning systems condition, than in the guideline daily system. Based on the parents, the guideline daily amount system was associated with higher healthfulness scores, and warning labels had more impact on ratings than other labels, while the labels influenced children less.
24	2017	Yoo et al. [71]	Participants were exposed to several fictive products with different combinations of (a) dairy products (yogurt, chocolate-flavored milk, and vanilla milk dessert), (b) sugar reduction claim (present or absent), and (c) traffic light system (present or absent); presented with the products one at a time and instructed to rate how much they would like the product. The results show that participants were influenced by product type, sugar reduction claim, and traffic light system from most to least in that order.

Table A3. *Cont.*

Article	Year of Publication	Author(s)	Findings
25	2020	Shin et al. [15]	Consumers shopped in an online grocery store and were exposed to either (a) dynamic food labels with real-time feedback based on selected products in a virtual basket or (b) no food label condition; consumers' purchases were used to derive weighted average Nutri-score per serving, total calories and sugar purchased, calories per dollar purchased, and average servings of calories, sugar, sodium, total fat, and saturated fat. The results show that the average Nutri-score was higher, and all other measures were lower for participants in the label condition than the participants in the no label condition.
26	2018	Acton et al. [33]	Participants were allocated to (a) numeric rating food label, (b) health star rating, (c) simplified traffic light symbol or, (d) no label condition; presented with three beverages with varying degrees of healthiness, all of them which had the label corresponding to the condition; and were instructed to rate the healthiness of the product. The results show that participants exposed to health star rating were more likely to select moderately healthy for moderately healthy beverages, than when exposed to other labels.
27	2020	Rojas-Rivas et al. [72]	Participants were exposed to pairs of products with different combinations of type of bread (white or whole wheat), brand (unknown or known), sodium warning (present or absent), and price (75, 85, or 100USD); and instructed to select between the two products or a "none of these breads" option. The results show that participants were influenced by sodium warning, brand, and type of bread from most to least in that order, although the type of bread was not statistically significant.
28	2021	Yang et al. [73]	Participants were exposed to two food products with different combinations of (a) types of health labels, (b) types of low-carbon labels, (c) proportions of brown to white rice, (d) cooking method, and (e) price; and were instructed to select which one they prefer. The results show that health and low-carbon labels in the form of symbols were associated with a higher willingness to pay than brief text claims about health or low-carbon. All labels had higher impact on choice than cooking method but lower than the proportion of brown to white rice.
29	2021	Mauri et al. [74]	Study 1: Participants were exposed to two foods with (a) two or six sugar teaspoons labels and (b) red or green traffic light labels and were instructed to select the product that best reflects their preference. Study 2: Participants were allocated in either (a) traffic light label condition, (b) sugar teaspoons label condition, or (c) no label condition; they were instructed to select one of three products that they would like to buy. After the selection, the ingredients of the products with different degrees of simplicity were shown. Participants were instructed to rate their preference for labels, ingredient information, and degree of the healthiness of the product. These studies show that labels had a small increase in healthier food selection. Participants exposed to sugar teaspoon labels chose, on average, a higher proportions of healthy foods than participants exposed to traffic light labels. In addition, the effects of sugar teaspoons are also impacted by food category, and ingredient composition influences ratings of healthiness.

Table A3. *Cont.*

Article	Year of Publication	Author(s)	Findings
30	2020	Jin et al. [75]	Study 1: Participants were allocated to either (a) physical activity equivalent calorie label condition or (b) no label condition; instructed to rate how hungry they were, exposed to a food product, instructed to consume the product, rate how much they liked the product and their dieting tendencies, and to run on a treadmill for as long or as intensely as they chose. Study 2: Participants were allocated similarly to in study 1, used another food product, were instructed to complete a lexical decision task consisting of non-words, neutral words unrelated to energy balance, target energy balance-related words, and were later instructed to run on a treadmill as in study 1. Study 3: Participants were allocated to (a) presence of label and energy-balance tasks, (b) presence of label and absence of energy-balance task, (c) absence of label and presence of energy-balance task, or (d) absence of label and energy-balance task conditions; instructed to conduct a language test, to construct a four-word sentence and, similarly as to previous studies, taste food and run on a treadmill. These studies show that participants with high dietary tendencies consumed fewer calories and burned more calories in the treadmill condition compared to non-dieters, that such effects were greater for dieters compared to non-dieters, that such labels affect response time to energy balance-related words in a higher degree to dieters compared to non-dieters, and that dieters in the presence of label and absence of energy-balance conditions had higher energy expenditures compared to absent of energy-balance condition.

Note. Each included article is shown in the first column, while the findings of the articles are presented in the last column. The findings of each article are summarized by the participants, intervention, comparison, outcome (PICO), and results.

Table A4. The effects of physical and digitalized FOP food labels.

Dependent Variable Was Affected by the FOP Format	Physical	Digitalized		
		Static	Interactive	Technology-Enabled
Full	83.3% (4, 9, 11, 26, 30)	83.3% (6, 7, 12, 15, 16, 18, 24, 27, 28, 29)	60% (1, 3, 14)	100% (25)
Partial	16.7% (10)	16.7% (17, 22)	20% (20)	0%
No	0%	0%	20% (5)	0%
Total number of articles	6	12	5	1

Note. The table shows the percentage of articles that indicate that the dependent variable was under full, partial, or no control as a function of physical, all digitalized, digitalized static, interactive, and technology-enabled FOP food labels. Articles that contained a study that did not have an absence of FOP food label conditions were not included in this table. The numbers in the parentheses correspond to the article number included in the review. The total number of articles which investigated physical, digitalized static, interactive, and technology-enabled FOP food labels are shown in the last row.

Table A5. Risk of bias assessment for included articles that used randomized control trials.

		Before Study	During Study			After Study		
Article	Study	Randomization Process	Deviations from Intended Interventions	Missing Outcome Data	Measurement of Outcome	Reporting of Results	Carryover or Timing Effects	Overall Risk of Bias
1		Low	Low	Low	Low	Low	Low	Low
3		Low	Low	Low	Low	Moderate	Low	Moderate
4		Low	Low	Low	Low	Moderate		Moderate
5		Moderate	Low	Low	Low	Moderate		High
6		Moderate	Low	Low	Low	Moderate		High
7		Low	Low	Low	Low	Moderate		Moderate
8	Study 2	Low	Low	Low	Low	Moderate		Moderate
10		Moderate	Low	Low	Low	Moderate	Moderate	High
11		Low	High	Low	Moderate	Moderate		High
12		Moderate	Moderate	Low	Low	Moderate	Moderate	High
14		Low	Low	Low	Low	Moderate		Moderate
15		Low	Low	Low	Low	Moderate		Moderate
16		Low	Low	Low	Low	Moderate		Moderate
18	Study 2, 3, and 4	Moderate	High	Low	Low	Moderate		High
19		Moderate	Low	Low	Low	Moderate		High
20		Low	Moderate	Low	Low	Low	Low	Moderate
22		Moderate	High	Low	Low	Moderate		High
23		Moderate	Low	Low	Moderate	Moderate		High
25		Low	Low	Low	High	Moderate	Low	High
26		Moderate	Low	Low	Moderate	Moderate		High
29	Study 2	Low	Low	Low	Low	Moderate	Moderate	High
30	Study 1, 2, and 3	Moderate	Low	Low	Low	Moderate		Moderate

Note. Each included article is shown vertically, while the risk of bias assessment based on the RoB 2 tool domains is shown horizontally.

Table A6. Risk of bias assessment for included articles that used non-randomized control trials.

Article ID	Study	Temporal Order of Independent Variable and Effect	Participant Characteristics across Groups	Procedure for Interventions	Control Condition	Multiple Measurements of Outcome Pre- and Post-Intervention	Missing Data	Measurement of Outcome	Reliability of Outcome	Appropriate Analysis	Overall Risk
2	Study 1 and 2	Low	Low	Low	High	High	Moderate	Low	Low	Low	High
9		Low	Low	Low	Low	Moderate	Moderate	Low	Low	Low	High
13	Study 2	Low	Low	Low	Moderate	Moderate	Moderate	Low	Low	Low	High
17		Low	Low	Low	Low	High	Moderate	Low	Low	Low	High
18	Study 1	Low	Moderate	Low	Low	High	Low	Low	Low	Low	High
21		Low	Low	Low	Low	Low	Low	Low	Low	Moderate	Moderate
24		Low	Low	Low	Low	Moderate	Low	Low	Low	Low	Moderate
27		Low	Low	Low	Low	Moderate	Low	Low	Low	Low	Moderate
28		Low	Low	Low	Low	Moderate	Low	Low	Low	Moderate	High

Note. Each included article is shown vertically, while the risk of bias assessment based on the adapted JIB tool is shown horizontally.

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Information, ingestion, and impulsivity: The impact of technology-enabled healthy food labels on online grocery shopping in impulsive and non-impulsive consumers

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Introduction: Unhealthy food consumption is a problem for society, companies, and consumers. This study aims to contribute to knowledge regarding such issues by investigating how technology-enabled healthy food labels can impact food choice in an online grocery store context. We conceptualized unhealthy and healthy food choice as a matter of impulsivity problems. Three technology-enabled healthy food labels were derived based on variables that might impact self-control, and their influence on food choice was investigated.

Methods: The empirical study consisted of three parts. In the first part, participants' impulsivity was measured using an adjusting delay task. Part two investigated the effects of self-monitoring, pre-commitment, and social comparison-based technology-enabled healthy food labels on food choice in a hypothetical online grocery shopping setting using a choice-based conjoint experiment. Lastly, in the third part, three where demographical questions were asked.

Results: The results (n = 405) show that self-monitoring, pre-commitment, and social comparison-based technology-enabled healthy food labels had the most to least impact on food choice in that order. Furthermore, the results indicate that self-monitoring and pre-commitment labels had more impact on the choice for impulsive compared to non-impulsive participants. Similarly, the results indicate that social comparison had more impact on choice for non-impulsive participants. These findings suggest that self-monitoring of previous healthy food choices might be more effective than pre-commitment based on discounts for healthy food products. However, these differences were minor.

Discussion: This finding has managerial implications as grocery stores might increase their revenue by introducing self-monitoring labels in an online grocery shopping setting. Future research should investigate these technology-enabled healthy food labels in natural food purchase settings.

KEYWORDS

consumer behavior, technology, food labels, online grocery, delay discounting, impulsivity

1. Introduction

Obesity is a problem worldwide. There is an increasing number of obese individuals across age, sex, geographical location, ethnicity, and socioeconomic status (1). There are now more obese than underweight individuals (2). It is associated with numerous diseases (3) and is a significant economic burden for society (4). Furthermore, a large body of evidence suggests that the food environment impacts obesity (5). As a result, the food industry is now receiving pressure from governments worldwide to decrease sales of unhealthy food products. This may lead to stricter government policies, such as introducing nutritional warning labels on food products if retailers, food manufacturers, and marketers do not adapt. In addition, it may limit consumers' product options. In contrast to this hard strategy, companies may nudge consumers to purchase healthier options without restricting their food choices by altering the purchase situation (6). One proposed strategy for increasing healthier food choices is simplified front-of-package food labels (7) that signal how healthy a food product is. However, such labels do not always increase healthy food purchases, although such labels do help consumers identify which products are healthy (8, 9). Further, such labels may impact people that are obese differently than people who are not obese (10). Hence, identifying possibilities of new healthy food labels may be one way to increase healthy food purchases, and this has academic, managerial, and societal value.

Technology-enabled labels that present specific information may help consumers to commit to healthier food options over unhealthier food options. Specifically, they may be presented to increase healthy food purchases. These technology-enabled healthy food labels may provide personalized, dynamic, and real-time based information regarding the healthfulness of products in point-of-purchase situations (11). For instance, Shin et al. (12) investigated the effects of dynamic displays of technology-enabled labels on healthy food purchases in an online grocery store setting. They found that these labels were effective in increasing healthy food purchases. Furthermore, Fuchs et al. (13) investigated the effects of tailored food labels on self-reported intention to use and performance expectancy. Specifically, different scores regarding healthy foods were given depending on gender, age, physical activity levels, and body-mass index of participants. They found that such labels were perceived as more helpful, relevant, and recommendable than non-tailored healthy food labels.

One may present different technology-enabled healthy food labels to consumers based on their behavior, and one may present different labels for impulsive and non-impulsive consumers in an online grocery store context. Research shows that some behaviors are associated with obesity (14), and one of these behavioral predictors may be impulsivity (15). Impulsivity can be viewed as a *trans*-disease, as impulsive behaviors may lead to obesity, substance abuse, and other behavioral problems. As proposed by Foxall (16), in the context of impulsivity, consumer behavior may be on a continuum from routine to extreme consumer choice. Furthermore, Foxall (17) suggests that consumer behavior models that incorporate environmental factors may provide more predictive power compared to models that do not take these into consideration. Building on this, one may use choice experiments to identify environmental variables that may increase healthy food choice (18), and examine whether some environmental factors are more effective for increasing healthy food choice for impulsive and non-impulsive consumers than others. There exists some research suggesting that the purchase of food products in an online grocery store context results in healthier choices compared to offline grocery stores (19). However, this effect may occur due to delivery time, as consumers have to wait after making the order before receiving the products. This effect may not occur if the delivery time is made shorter if online grocers become more effective in reducing delivery time. Hence, online grocers may create technology-enabled healthy food labels that use variables that increase self-control to increase healthy food purchases and provide personalized technology-enabled healthy food labels for impulsive and non-impulsive consumers.

There exist several knowledge gaps in the literature related to the effects of healthy food labels. For instance, few research articles exist on technology-enabled healthy food labels and how they impact consumer behavior despite existing theoretical literature on incorporating psychological variables in food labeling (20). Furthermore, there exist studies that have investigated how impulsivity impacts the effects of food labels on consumer behavior (21–23). However, there is little research on this in an online grocery store setting. Most of these studies have used participants' self-reported measurements of impulsivity rather than using choice behavior. Impulsivity measured by self-reports may produce different results than choice behavior (24). In addition, implementing technology-enabled healthy food labels may provide several benefits for companies, consumers, and society. For companies, such labels may create a competitive advantage by increasing healthy food sales, build brand equity, and generating positive word-of-mouth that may attract new customers. For consumers, it may increase health benefits and well-being. For society at large, it may reduce obesity rates and the concomitant economic burden. Hence, research regarding technology-enabled healthy food labels has significant societal and academic value. This paper thus aims to contribute to the body of knowledge by providing such research. The research questions of this study are as follows:

Research question 1: What is the relative impact of (a) self-monitoring-based, (b) pre-commitment-based, and (c) social comparison-based technology-enabled healthy food labels on choice behavior in a hypothetical grocery shopping setting?

Research question 2: How does the relative impact of these technology-enabled healthy food labels on choice behavior differ for impulsive and non-impulsive consumers?

The rest of the paper is structured as follows. First, a literature review and hypotheses for this paper are provided. Second, the methodology and results of this paper are presented. Third, findings and discussion are given. At last, implications and further research directions are explored.

Impulsivity may be measured by delay discounting. Delay discounting refers to the phenomenon where the value of a reward decreases as a function of increasing the delay to receive the reward (25). This relationship can be expressed by the hyperbolic formula presented in Equation 1 for delay (26):

$$V = \frac{A}{(1 + kD)}$$

V is the subjective value of receiving a reward, A is the objective amount, D is the delay to receive the reward, and k is an empirically derived free parameter that determines the steepness of the subjective value. A higher k generates a steeper subjective value as a function of increasing delay than does a smaller k value. Typically, such functions are derived by asking individuals to make choices between receiving immediate and smaller or delayed and larger rewards, and then adjusting either the delay or amount. Participants' indifference points between these two options are obtained and are used as a measure of empirical subjective value. Equation 1 has been shown to be more predictive of how the subjective value of a reward decreases as a function of delay than other models (e.g., traditional discounted utility model) and may describe preference reversals (27). Furthermore, some variables that moderate the effect of the probability of receiving a commodity on subjective value (probability discounting) may also be the same as variables that moderates the impact of the delay to receive a commodity on subjective value. However, evidence that these two constructs are the same phenomenon is small or moderates (28). In delay discounting, when the k-value is high, future events are discounted more than with lower k-values. Thus, impulsivity may be measured using k-values, as high k levels correspond to higher levels of impulsivity, while low k levels correspond to higher levels of non-impulsive (i.e., self-controlled) behaviors (for measurements of impulsivity see (29)).

High discounting rates are correlated with problematic health-related outcomes such as obesity and substance abuse (30), and discounting rewards depend on several factors. For instance, impulsivity may be due to genetic factors, as individuals who discount one commodity also tend to discount other commodities. However, it may also be influenced by current environmental factors. For instance, which type of reward is used (31, 32), cultural factors (33–35), and question framing (36, 37) may alter discounting rates. As exemplified by the Ainslie-Rachlin principle (38), there is a higher probability of choosing the immediate and smaller reward when the time between making a choice and receiving the reward is short. However, there is a higher probability of choosing the delayed and larger reward when both rewards are delayed by a constant. Using this knowledge, consumers may use external commitment devices to commit to choices that produce larger later rewards.

Delay and probability discounting have been used to investigate several factors influencing consumer behavior. For instance, it has been used to investigate the relationship between delivery fees and delay in e-commerce (39); rebates and for high and low-pricing products (40); online reviews and prices (41); hunger and discounting of food and non-food commodities (42). With regard to healthy food consumption, variables that may impact delay discounting may also impact healthy food choice (43). In accordance with this framework, there exists research that suggests that higher delay discounting of hypothetical momentary rewards is correlated with the purchase of unhealthy food products (44, 45) and that increasing delay for unhealthy foods may be used to increase the value of healthy food purchase (43).

Several systematic reviews and meta-analyses have identified that self-monitoring, pre-commitment, and social factors may increase non-impulsive behaviors (46–48). However, few studies have investigated how such strategies in the form of technology-enabled healthy food labels affect consumers at the point of purchase, and few have investigated their relative impact on choice behavior. For this study, the effects of technology-enabled healthy food labels that present self-monitoring of previous healthy food choice, pre-commitment options, and other consumers' healthy food purchases on food choice behavior was investigated in point-of-purchase situations in a hypothetical online grocery store setting.

Self-monitoring refers to the recording and presentation of one's own previous behavior to promote behavior change. Self-monitoring can function as a form of soft commitment (49). Specifically, observing one's own previous patterns of choices may moderate the effects of long-term consequences on choice behavior without altering the immediate consequences of individual choices. Self-monitoring can be done actively, where individuals are required to record their behavior manually, or passively, where individuals may be presented with their own behavior history that is automatically recorded by a device. Research suggests that instructing individuals to actively record their choices may promote an increase in healthy food choices, and this has been investigated by using different technologies. For instance, Teasdale et al. (50) conducted a meta-analysis on remotely delivered strategies that used self-monitoring and tailored feedback and their effect on eating behavior. The strategies were delivered using paper reports, letters, booklets, and computers, and their results suggest that such strategies had a positive impact on eating behavior. Furthermore, Bartels et al. (51) conducted a systematic review of the effects of digital self-monitoring on improving health in middle-aged or older adults. The strategies were delivered using interactive voice response through using dials on telephones, personal digital assistants, short message services (SMS), smartphone apps, and computers. Their results show that most of the studies across behaviors lead to a change in at least one outcome measurement, including food and water consumption. Lim et al. (52) conducted a systematic review of the effects of technology apps to promote healthy food purchases and consumption. The devices that provided the strategies were mostly smartphones, and some used personal digital assistants. Their results show modest evidence for the efficacy of such strategies in improving healthy food purchase and consumption. These authors suggest that further research should explore passive automatic and personal feedback, that such digital health strategies could be incorporated into supermarket loyalty cards, and that real-time self-monitoring, feedback, and social incentives may increase healthy food choices. Hence, passive self-monitoring may be more effective in increasing the effects of long-term healthy food choices than active self-monitoring. One possible mechanism for this effect is that the presentation of previous higher values of non-impulsive behaviors may increase the probability of current non-impulsive behaviors. In addition, one may assume that non-impulsive individuals are more likely to be impacted by the presentation of their patterns of previously healthy food choice compared to impulsive individuals. This assumption is based on that non-impulsive behavior may be under the influence of temporally extended contingencies (49), such as environmental events that occur as a function of patterns of choices. Based on this, the following hypotheses are proposed:

> H1: The presentation of food products in combination with higher values of prior healthy food choices for such products increases the probability of choosing of such products compared to their absence.

> H2: The effects described in H1 will be greater for non-impulsive consumers than impulsive consumers.

Pre-commitment may refer to the voluntary act of changing the immediate consequences of individual choice to set the occasion for choosing larger-later rewards. Specifically, a commitment response that removes future available choices or that imposes a cost for certain choices (53, 54) in order to promote behavior change may be one way of defining pre-commitment. For instance, when consumers prefer healthy over unhealthy food when the time between making a choice and receiving the reward is large, then they can use hard commitment devices that provide additional consequences of their future individual choices. There exist studies that have investigated the effects of pre-ordering healthy food purchases and choice. For instance, Stites et al. (55) investigated the combined effects of pre-ordering lunch online, mindful eating training, fat information, and price reductions on healthy food purchases by employers in a hospital. Their results show that individuals allocated to the treatment condition purchased on average fewer calories and fat content and had a higher degree of mindful eating than individuals in the control condition. Similarly, Miller et al. (56) investigated the effects of pre-ordering compared to pre-ordering with a behavioral nudge. The nudge consisted of messages suggesting that all the components of a healthy meal or messages stating that the participants had selected a balanced meal if they selected all the healthy components. They found that participants in the pre-ordering condition had a higher average selection of fruit, vegetables, and milk products than individuals in the control condition. Furthermore, participants in the pre-ordering and behavioral nudge condition chose on average healthier products than the participants in the pre-ordering-only condition. Schwartz et al. (57) examined healthy food purchases as a function of pre-commitment by self-imposed aversive consequences. Specifically, households were enrolled in an incentive program that gave discounts on food products. The strategy consisted of an increase in the price of food products if they did not increase their prior healthy food purchase. Their results show that roughly one-third of the recruited households agreed to participate in the study. These households had higher healthy food purchases than the control group (and households that declined to participate). These studies suggest that pre-commitment may increase healthy food purchases. However, little research exists on the relationship between pre-commitment and the choice of healthy products for impulsive and non-impulsive consumers. In addition, one may assume that immediate environmental variables that may alter choice are more impactful for impulsive consumers than non-impulsive consumers. This assumption is based on that impulsive behavior may be under the influence of temporally narrow contingencies (49). Based on this, the following hypotheses are proposed:

> H3: The presentation of food products in combination with pre-commitment to healthy food choice will increase the probability of choice for such products compared to the absence of pre-commitment.

> H4: The effects described in H3 will be greater for impulsive consumers compared to non-impulsive consumers.

Social proof refers to the phenomenon whereby individuals tend to copy other people's behavior when they are uncertain regarding what choices are correct in a given situation (58). Research has examined how social proof in the context of information sources, social identity, and self-control may impact healthy food choices. However, few articles have examined the effects of personalized healthfulness information on food basket choice when it is low or high compared to other consumers' choices. Sigurdsson et al. (59) investigated the effects of different sources of social proof on the hypothetical choice and purchase of fresh fish. Specifically, the quality of the product was based on other consumers' ratings by using a "Top Seller" label or authoritative sources by using a "Store's Choice" label. Their first and second study found that other consumers' ratings had more impact on choice behavior in hypothetical online grocery and brick-and-mortar store settings. Their third study found that both labels were effective in increasing sales of fresh fish and ground beef. Furthermore, Liu et al. (60) investigated the effectiveness of social norms on eating behavior as moderated by social identity. They found that social-proof messages regarding healthy foods were effective in increasing self-reports regarding healthy eating behavior for individuals who identified with the social group that the message referred to. Furthermore, Salmon et al. (61) investigated the effects of social proof on low-fat cheese purchases of consumers with high or low self-reported self-control. Their study induced high or low self-control by using an ego-depletion. Their results show that social proof increased the average percentage of low-fat cheese purchases consumers allocated to the ego-depletion task compared to controls. However, individuals who did not perform the ego-depletion task purchased, on average less low-fat cheese. The authors suggest that high self-control individuals may have purchased other healthy food products and that these results do not necessarily show a negative effect of purchase behavior for highly self-controlled consumers. However, these results have been produced by another similar study. Gonçalves et al. (62) investigated the effects of social proof on fruits and vegetables purchases of soft, medium, and hard buyers of fruits and vegetables. Their results show that social proof increases healthy food purchases for all consumers except hard buyers. These articles indicate that social comparison presented by other consumers' purchases increases food choices in impulsive consumers. In addition, consumers who already purchase healthy food may be assumed to have higher self-control than individuals who do not. Based on this assumption, social comparison may be more effective for impulsive consumers and may not be effective for non-impulsive consumers. Based on these studies, the following hypotheses are proposed:

> H5: The presentation of food products in combination with higher values of social comparison increases the probability of choice of such products compared to the absence of social comparison in impulsive consumers.

> H6: The presentation of food products in combination with higher values of social comparison decreases the probability of choice of such products compared to the absence of social comparison in non-impulsive consumers.

2. Materials and methods

2.1. Participants

Four hundred and twenty-three participants were recruited by using the crowdsourcing platform Prolific. The sample that was selected by the service was a balanced sample of citizens in the United Kingdom. This sample size is considered appropriate for conjoint experiments (63, 64). The participants were invited to participate in a consumer choice study for £8 per hour with an estimation of 15 min to complete the study. They were required to read and sign an informed consent form regarding their rights as participants in an experiment before joining the experiment. They were told they could leave the experiment at any time during the study. This study has been assessed that to be in accordance with the Norwegian privacy legislation by The Norwegian Agency for Shared Services in Education and Research.

2.2. Setting, materials, and apparatus

The experiment was performed using several online and computer services. First, Prolific was used to recruit and administer the link to the experiment to the participants. Second, Sawtooth Software Lighthouse Studio 9.14.2 was used to record the participants' choices, present the procedure, and conduct data analysis. Third, Excel, RStudio, and the ggplot2 package were used for data analysis and visual representation of the data. This study was first pre-tested with 102 participants and later a second test with 303 participants, resulting in a total of 405 participants.

2.3. Procedure

The procedure consisted of three parts which were presented in the following order. The first part consisted of a 5-trial adjusting delay task (65) and was used to measure the participants' impulsivity. In the second part, the three technology-enabled healthy food labels were introduced and then a choice-based conjoint experiment (63) was used to assess their relative impact on choice behavior. The third part consisted of asking demographic questions. The study was pre-tested by using the Sawtooth Software random response simulation. The authors provided a link to the experiment using Sawtooth Software servers to each participant by using the Prolific platform.

2.3.1. Adjusting delay task

Participants were required to read the following instructions: "*The study consists of three parts. The purpose of the first part is to examine your economic choices. You will be presented with several hypothetical scenarios that consist of two options each. Choose the option that you prefer by clicking on it. Press 'Next' to continue.*"

The 5-trial adjusting delay task consisted of presenting five trials each consisting of two hypothetical options. In all trials, participants were asked to choose between receiving hypothetical rewards of £50 now or receiving £100 in combination with a delay. The delayed reward was changed based on their previous choices. The delay in receiving the hypothetical reward in a trial was reduced if in the previous trial the participants chose to receive the reward now or increased if the participant chose to receive the reward later. The specific levels of delay in all trials are shown in **Figure 1**. The participants were required to choose one of two options before proceeding to the next trial. The participants could not go back to the previous trial once they submitted their answers, and the order of the options was randomized.

2.3.2. Technology-enabled healthy food labels and choice-based conjoint experiment

After completing the adjusting delay task, participants were introduced to three technology-enabled healthy food labels and their relative effect on choice of food baskets in different hypothetical online grocery stores was examined. They were presented with the following introduction in part two: "*You have now finished the first part of the study, and you must now check off this box to confirm the end of part one. Part two will examine your preference regarding online grocery shopping. Press 'Next' to proceed.*"

They were later presented with the following instructions: "*Imagine that you are about to order a food basket by using an online grocery store. In these scenarios, you decide to compare three different online grocery stores before deciding which to choose. Each scenario has labels that will help you in the choice process.*" The participants were later presented with three technology-enabled healthy food labels successively. They were first presented with a symbol, then

Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	k-value	Category
				Now	24,0000000	1
			Now	1 hour	17,0000000	2
			2 hours	Now	9,7900000	3
		Now		3 hours	6,9300000	4
		4 hours		Now	4,9000000	5
	Now		Now	6 hours	3,2700000	6
			9 hours	Now	2,3100000	7
				12 hours	1,4100000	8
				Now	0,8160000	9
			Now	1.5 days	0,5770000	10
	1 day		2 days	Now	0,4080000	11
Now		Now		3 days	0,2890000	12
		4 days		Now	0,1890000	13
			Now	1 week	0,1170000	14
			1.5 weeks	Now	0,0825000	15
				2 weeks	0,0583000	16
				Now	0,0396000	17
			Now	1 month	0,0232000	18
			2 months	Now	0,0134000	19
		Now		3 months	0,0094900	20
3 weeks		4 months		Now	0,0067100	21
	Now		Now	6 months	0,0047410	22
			8 months	Now	0,0033500	23
				1 year	0,0019400	24
				Now	0,0011200	25
			Now	3 years	0,0007910	26
	2 years		4 years	Now	0,0006120	27
		Now		5 years	0,0004330	28
		8 years		Now	0,0002790	29
			Now	12 years	0,0001860	30
			18 years	Now	0,0001290	31
				25 years	0,0001100	32

FIGURE 1
Overview of the adjusting delay task. This figure shows the hypothetical scenarios regarding the adjusting delay task. The trial number is indicated at the top. The initial delay during trial 1 was always three weeks. In trial 2, the participants were given the upper scenario if they selected now in trial 1 or were given the lower scenario if they selected three weeks in trial 1. The remaining trials had similar branching depending on the previous choice. K-values and the categories are specified on the right.

text that explained the symbol, and lastly, with a test that required them to match the symbol and the prior text.

For the introduction to the Streak label, the participants were shown an image of a blue square, and they were told that this was the healthy Streak label and instructed to press "next" to continue. Later, they were presented with the same image with the following text underneath. "*This label shows how many previous healthy orders in a row you have made. In this case, a healthy order is defined as having at least 50% of items in the basket that are labeled healthy by the Traffic Light Food Labelling System. If you choose this basket, you continue your healthy streak.*" They were required to press "Next" to continue during the presence of this text. Next, the participants were presented with the same square with three multiple-choice options. One of the options was the same text as during the introduction of the Streak label. Participants who selected this option were told they were correct and proceeded to the condition that presented the next label. Participants who selected either of the other two options were told that their answers were incorrect, redirected to the blue square, and the procedure was repeated.

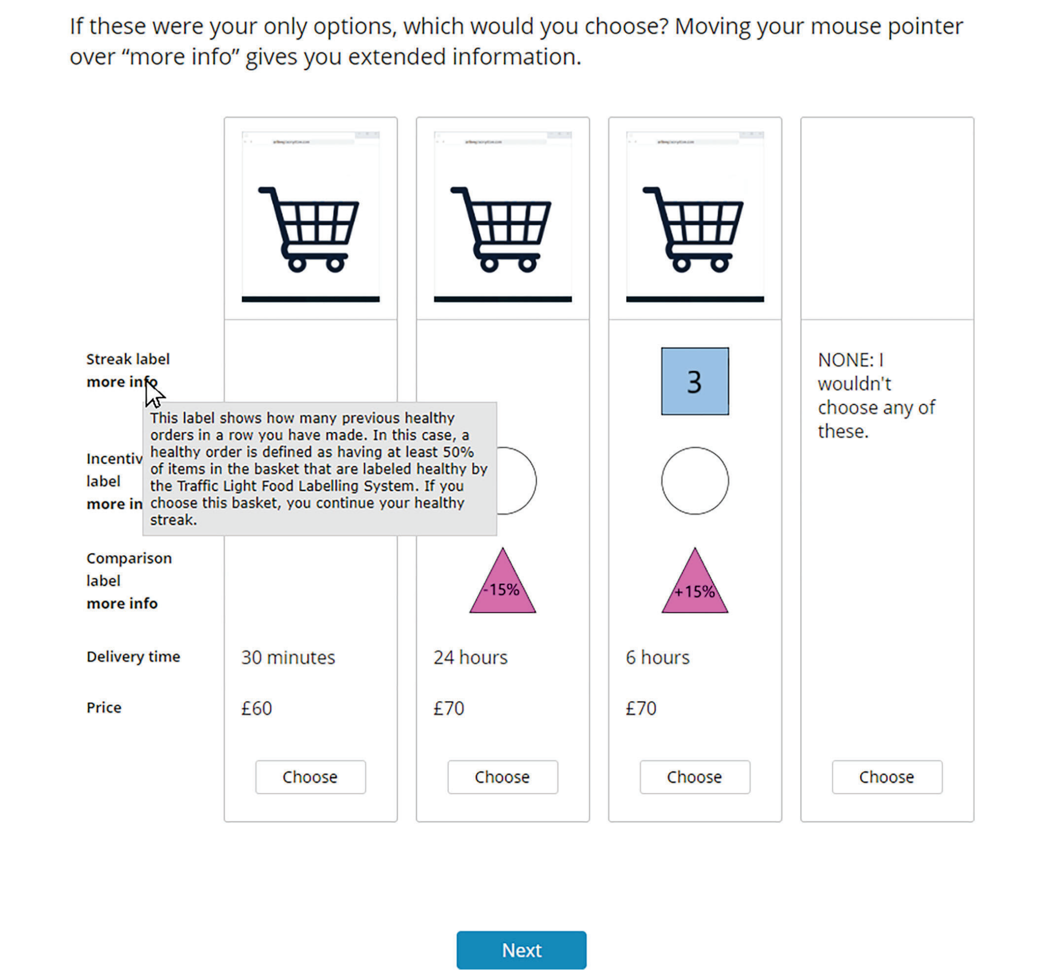

FIGURE 2
Example of a trial in the choice-based conjoint experiment. This figure shows an example of a choice trial in the choice-based conjoint experiment. The independent variables are on the right and the specific levels within each profile are indicated.

For the introduction to the Incentive label, the participants were presented with an image of a white circle and they were told that this was the healthy Incentive label and instructed to press "Next" to continue. Later, the same image with the following text was presented: "*This label appears when you have a minimum of 30% fruits and vegetables in the basket. If you choose this option, you get a 10 % discount on this and your next purchase that also meets this requirement.*" Similarly, the participants were required to press "Next," after which three multiple-choice options were presented. Likewise, participants were redirected to the label's introduction if they selected options other than the original text. They continued to the next section if they selected the original text.

For the introduction to the Comparison label, the participants were presented with a pink triangle and were told that this was the healthy Comparison label and instructed to press "Next" to continue. Later, the same image with the following text underneath was presented: "*This label shows the percentage of groceries in your basket that are labeled healthy by the Traffic Light Food Labelling System ® compared to what other consumers in your area have bought.*" *Similarly, three multiple-choice options were presented after selecting "Next"*. Likewise, participants were redirected to the label's introduction if they selected options other than the original text. They continued to the next phase if they selected the original text. The text of the multiple-choice options is shown in Appendix A. All options were presented in random order.

The participants were presented with a choice-based conjoint experiment right after the introduction to the labels. A conjoint experiment consists of a combination of generating experimental design and the usage of multivariate statistics to investigate the relative impact of multiple independent variables (63). Specifically,

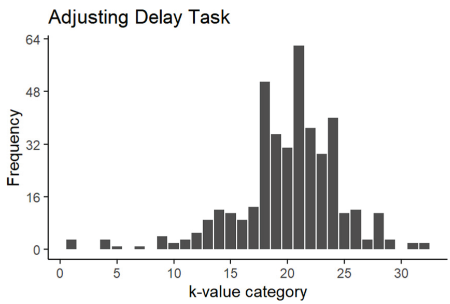

FIGURE 3
Results from adjusting delay task. This figure shows the frequency of each participant across the 32 different k-value categories. The frequency is indicated on the vertical axis and the k-value categories are indicated on the horizontal axis. Higher k-values are represented on the left, while lower k-values are represented on the right side of the graph.

it consists of generating combinations of several values of independent variables, and their effect on decision-making is then evaluated. In a choice-based conjoint experiment, several profiles are presented and the participants are instructed to choose one among these profiles. In this study, the participants were presented with a choice-based conjoint experiment with several profiles within a trial, and their choices regarding these profiles were recorded. Each profile had information associated with it; this information was the independent variables in this study. This study used a full-profile method that presented all the independent variables simultaneously when a profile was presented. The choice trial consisted of three profiles and a "None" option where the latter was always positioned to the right. The participants had to select one of four options and press next to proceed to the "Next" trial. Each participant was presented with 12 choice trials, and the order of the trials was randomized to rule out order effects (66). A balanced overlap method was used to design the profiles (67). This method consists of generating choice trials where the profiles have combinations of values of independent variables that have low correlation. By using this method, the software (Lighthouse Studio 9.14.2) generated 300 different sets and each set had 12 choice trials. Each participant was presented with one of these 300 sets. The participants could access the information of each label provided in the instructions by hovering their cursor over the "more info" text underneath the names of the independent variables. An example of a trial is shown in **Figure 2**. The participants were presented with the following instruction before the choice-based conjoint experiment and between the 12 trials: "*You will now be presented with the 1st out of 12 different hypothetical purchase situations. These situations are independent of each other, and your choices in one situation do not impact the next. Thus, answer as you would have done in a real-life purchase situation.*" The instructions specified which trials were presented (i.e., 1st, 2nd, 3rd, ... 12th).

2.3.2.1. Independent variables

Five independent variables were used. Three of these were self-monitoring, pre-commitment, and social comparison based technology-enabled healthy food labels. Two additional independent variables were added to increase the realism of the choice experiment: delivery time and price.

First, the self-monitoring independent variable consisted of the following levels: "blank," "square with number 2," and "square with number 3."

Second, the pre-commitment independent variable consisted of the following levels: "blank" and "circle."

Third, the social comparison independent variable consisted of the following levels: "blank," "triangle with −15%," and "triangle with +15%."

Fourth, the delivery time independent variable consisted of the following levels: "30 min," "6 h," and "24 h." These levels were derived by examining the earliest delivery time options of five online grocery stores in London, England.

Fifth, the price independent variable consisted of the following levels: "£60," "£70," and "£80." These levels were derived by examining the average amount spent per basket in English online grocery stores. These levels were set lower than the average amount spent per basket to decrease "None" option choices.

2.3.2.2. Dependent variable

The dependent variable was choice behavior among profiles within a trial.

2.3.3. Demographical questionnaire

After completing the choice-based conjoint experiment, participants were asked questions regarding their gender, age, household status, personal income last year, frequency of previous online shopping, product categories purchased online, frequency of purchasing food online, and food allergies.

2.4. Data analysis

Several data analysis methods were used. First, the frequency of participants across k-value categories was analyzed. Second, impulsive and non-impulsive individuals were classified by ranking them from high to low k-values according to the adjusting delay task. The half with the highest *k*-values were impulsive individuals, and the other half with the lowest *k*-values were defined as non-impulsive individuals. Three participant groups were formed, and these were based on (a) all participants, (b) impulsive participants', and (c) non-impulsive participant. All of the groups' data were used for statistical analyses. Second, logistic regression and Hierarchical Bayesian modeling based on aggregated data were used to estimate the impact of the independent variables and their levels on choice behavior. Logistic regression was employed by using maximum likelihood estimation for the main-effects of the relationship between binary choice behavior and the levels of the independent variables with five iterations. The regression coefficient for each level, standard error, and log-likelihood for the model was calculated. The importance score of the independent variables was calculated by taking the range of the regression coefficients of the levels within the independent variables and calculating the proportion of these values of one independent variable compared to the others. The impact of the independent variables for each participant was estimated using Hierarchical Bayesian modeling. This was done by estimating the impact of change at each level by using aggregate data of all participants and using such information to estimate the impact of each level for each participant. There were 20,000 iterations using this method, and the last 10,000 iterations were used for analysis. The average Hierarchical Bayes estimation for each level with standard deviation was estimated. Latent class analysis was performed by deriving two and three classes based on the results of the estimations. Finally, demographical data were provided for all three groups.

3. Results

Four hundred and twenty-three participants were invited to perform a study regarding consumer choice. Eighteen did not complete the survey, and their responses were removed from the analysis. The analysis was performed based on the remaining 405 participants in total. The average participant completed the study by in 526.47 s (8.77 min), with a range of 153–2,822 s (2.55–47.03 min), and a standard deviation of 290.77 (4.84 min).

The results from the adjusting delay task are shown in **Figure 3**. The figure shows that the category with the most participants was the 21st category (*k*-value = 0.0047), with a total of 62 participants. Based on these results, impulsive participants were defined as participants who completed the adjusting delay task and had a k-value of 24 to 0.0067 (from the 1st to the 20th category). Similarly, non-impulsive participants were defined as participants who completed the task and had a k-value of 0.0047–0.00011 (from the 21st to 32nd category.) As a result, 193 participants were classified as impulsive, and 212 were classified as non-impulsive.

The results of the demographic questions are shown in **Table 1**. Regarding all participants, the majority were males, and the most common age category was 25–34 years old. Most participants lived in a couple-household with children and had a personal annual income between £25,000 and £49,999. The majority shopped online once a week. Clothing and footwear were the most common items that were bought online, the majority of the participants bought groceries online at least once in a year, and the majority had no allergies. Regarding the impulsive participants, the majority were females, were between 25 and 34 years old, lived in a couple-household, had a personal annual income between £25,000 and £49,999, shopped online once every 2 weeks, bought online, majority of the participants bought groceries online at least once in a year, and had no allergies. Clothing and footwear were the most common type of products that were bought online. Regarding the non-impulsive participants, the majority were males, between 35 and 44 years old, lived in a couple-household, had a personal income between £25,000 and £49,999, and shopped online once a week. Books, music, movies, and games were the most common type of products bought online. Most participants bought groceries online at least once a year, and the majority had no allergies.

The results of the conjoint experiment based on all participants are shown in **Figure 4**. The results were the same when using logistic regression and Hierarchical Bayes estimation. Regarding the Streak label, the blue square with the number 3 was chosen more often than the blue square with the number 2, and the blue square with the number 2 was chosen more often than the absence of the Streak label. Regarding the Incentive label, the white circle was estimated to be chosen more often than the absence of Incentive labels. With regard to the Comparison label, the triangle with +15% was chosen more often than triangle with −15%, and the latter was chosen more often compared to the absence of the Comparison label. Regarding the delivery time, 30 min was chosen more often than 6 h, and the latter was chosen more often than 24 h. With regard to price, £60 was chosen more often than $70, and the latter was chosen more often than £80. The log-likelihood for the null model was −6,737.39, and the log-likelihood for the estimated model was −4,594.24, with a total difference of 2,143.15. In addition, the results from the logistic regression coefficients of the Comparison label based on impulsive participants were as follows: absent = −0.36, the triangle with −15% = −0.03, and the triangle with +15% = 0.39. The Hierarchical Bayes estimations for the same participants were as follows: absent = −0.70 (SD = 0.54), the triangle with −15% = −0.06 (SD = 0.91), and the triangle with +15% = 0.76 (SD = 0.74.) The logistic regression coefficients of the Comparison label based on non-impulsive participants were as follows: absent = −0.38, the triangle −15% = 0.03, and the triangle with +15% = 0.41. The Hierarchical Bayes estimations for the same participants were as follows: absent = −0.80 (SD = 0.67), the triangle with −15% = −0.11 (SD = 0.85), and the triangle with +15% = 0.92 (SD = 0.86.) The relative impact of the Streak label, Incentive label, Comparison label, delivery time, and price and Latent Class analyses based on these for all participants, impulsive participants, and non-impulsive participants are shown in **Figure 5**.

When comparing each group with itself, the results show a similar relative impact for all participants, including impulsive and non-impulsive participants. Specifically, price, Streak label, Incentive label, Comparison label, and delivery time had the most to least impact on choice in that order, using logistic regression and Hierarchical Bayes estimation. When comparing across the groups, the Streak label and incentive label had more impact on choice for impulsive participants than non-impulsive participants. Similarly, delivery time had more impact on impulsive participants compared to non-impulsive participants. In addition, price had less impact on choice for impulsive participants than non-impulsive participants. The log-likelihood for the null model based on impulsive participants was −3,210.66, and the log-likelihood model for the estimated model was −2,158.80, with a total difference of 1,051.85. The log-likelihood for the null model based on non-impulsive participants was −3,526,73, and the log-likelihood for the estimated model was −2,426.46, with a total difference of 1,100.26. When using three latent classes, the largest class shows that the Streak label and Incentive label had the most impact on choice, and the second largest shows that price and Incentive label had the most impact on choice for all participants, impulsive participants, and non-impulsive participants.

The results presented here support H1, H3, and H5, while the they do not support H2, H4, and H6. Specifically, the results show that higher values of prior healthy food choice, pre-commitment to healthy foods, and higher social comparison increase the probability of choice behavior compared to the absence of these labels. Furthermore, the latent class analysis and relative impact of these three independent variables (presented in **Figure 6**) did not identify segments that differed with regard to impulsive and non-impulsive participants. When using logistic regression coefficients and Hierarchical Bayes estimations of the impact of the Comparison label, the results showed no negative impact of

TABLE 1 The proportions of answers based on questions for all, impulsive, and non-impulsive participants.

Answers to the demographical questions	All participants (*n* = 405)	Impulsive participants (*n* = 193)	Non-impulsive participants (*n* = 212)
1. What is your gender?			
Male	50.12%	43.01%	56.60%
Female	49.63%	56.48%	43.40%
Non-binary / third gender	0.25%	0.52%	0.00%
Prefer not to say	0.00%	0.00%	0.00%
2. What is your age?			
18–24 years old	10.12%	10.88%	9.43%
25–34 years old	32.59%	35.75%	29.72%
35–44 years old	27.16%	23.83%	30.19%
45–54 years old	15.31%	16.58%	14.15%
55–64 years old	10.86%	9.33%	12.26%
65–74 years old	3.70%	3.11%	4.25%
75 years or older	0.25%	0.52%	0.00%
3. What type of household do you belong to?			
Couple household with children	40.99%	46.11%	36.32%
Couple household without children	29.63%	26.42%	32.55%
Single mother household	4.44%	5.18%	3.77%
Single father household	0.99%	0.52%	1.42%
Single person household	15.80%	13.99%	17.45%
Other	8.15%	7.77%	8.49%
4. Which of these describes your personal income last year?			
£0	0.99%	1.04%	0.94%
£1 to £9,999	12.84%	11.92%	13.68%
£10,000 to £24,999	29.63%	32.12%	27.36%
£25,000 to £49,999	39.01%	38.34%	39.62%
£50,000 to £74,999	9.63%	9.84%	9.43%
£75,000 to £99,999	0.74%	0.52%	0.94%
£100,000 or more	0.74%	0.00%	1.42%
Prefer not to answer	6.42%	0.62%	6.60%
5. How often do you shop online?			
Once a week	31.60%	29.02%	33.96%
Once every 2 weeks	26.42%	30.57%	22.64%
Once a month	19.26%	20.21%	18.40%
Around 3–4 times per quarter	12.35%	11.92%	12.74%
Once every 3 months	8.89%	7.77%	9.91%
I have not shopped online before	1.48%	0.52%	2.36%
6. What type of products have you bought online? Multiple answers are possible.			
Books, music, movies, and games	80.49%	77.20%	83.49%
Toys	50.62%	52.85%	48.58%
Consumer electronics and computers	72.10%	70.98%	73.11%
Sport equipment	39.01%	41.45%	36.79%

(Continued)

TABLE 1 (Continued)

Answers to the demographical questions	All participants (n = 405)	Impulsive participants (n = 193)	Non- impulsive participants (n = 212)
Health and beauty (cosmetics)	61.23%	64.77%	58.02%
Clothing and footwear	82.96%	83.94%	82.08%
Jewelry/watches	31.85%	33.16%	30.66%
Household appliances	65.43%	65.28%	65.57%
Do it yourself/home improvement	40.25%	36.27%	43.87%
Furniture and homeware	50.86%	51.30%	50.47%
Grocery	73.33%	75.13%	71.70%
None	0.49%	0.52%	0.47%
7. How often do you purchase groceries online?			
At least once in a year	35.56%	34.20%	36.79%
At least once in 6 months	20.74%	21.24%	20.28%
At least once in a month	26.91%	31.61%	22.64%
At least once a week	16.79%	12.95%	20.28%
8. Do you have any allergies?			
No	86.67%	84.97%	88.21%
Yes	13.33%	15.03%	11.79%

the triangle with +15% on choice behavior for non-impulsive participants.

4. Discussion

The main purpose of this study was to investigate whether choice behavior impacted by technology-enabled healthy food labels differed from impulsive and non-impulsive participants. Specifically, the relative impact of self-monitoring, pre-commitment and social comparison when presented as technology-enabled healthy food labels on choice behavior in a conjoint experiment was used. Impulsivity was measured through choice behavior by using an adjusting delay task.

This research contributes to two research fields. First, it relates to the emerging online grocery store and healthy food choice literature. Second, it relates to the general self-control literature and variables impacting healthy food choice. To the best of our knowledge, this is the first study to do so.

4.1. Internal validity

Overall, the results suggest that the self-monitoring, pre-commitment, and social comparison-based technology-enabled healthy food labels were the labels that had the most impact on choice behavior from most to least, in that order. In addition, the results indicate that self-monitoring and pre-commitment-based technology-enabled healthy food labels might be more effective for impulsive individuals than non-impulsive individuals. Furthermore, the results show that social comparison was more impactful on choice for non-impulsive participants than impulsive participants. However, clear segmentation based on latent class analysis regarding these results were not found, and definitive conclusions cannot be made based on these results.

With regard to self-monitoring-based technology-enabled healthy food labels, the results show that the presentation of higher values of prior healthy food choices increases choice behavior compared to its absence. Regarding pre-commitment-based technology-enabled healthy food labels, the findings show that the presence of pre-commitment to healthy food choice increases choice behavior compared to its absence. Furthermore, these results did not differ between impulsive and non-impulsive participants. With regard to social comparison-based technology-enabled healthy food labels, the results show that higher levels of social comparison increase choice behavior compared to its absence for impulsive participants. Lastly, the findings did not show that higher levels of social comparison decrease choice behavior compared to its absence for non-impulsive participants. In addition, the results from **Figure 5** indicate that impulsive participants' choices are more impacted by delivery time compared to non-impulsive participants and that non-impulsive participants are more price sensitive compared to impulsive participants. These results show some correspondence between the adjusting delay task and the choice-based conjoint experiment. Regarding the logit regression coefficients of the independent variables, all estimations had a standard error below 0.05 except for the "None" option. The highest standard error for the "None" option was observed for the impulsive participants, with a value of 0.09.

4.2. External validity

Consistent with prior research, this study identified segments of impulsive respondents whose choices were more impacted by

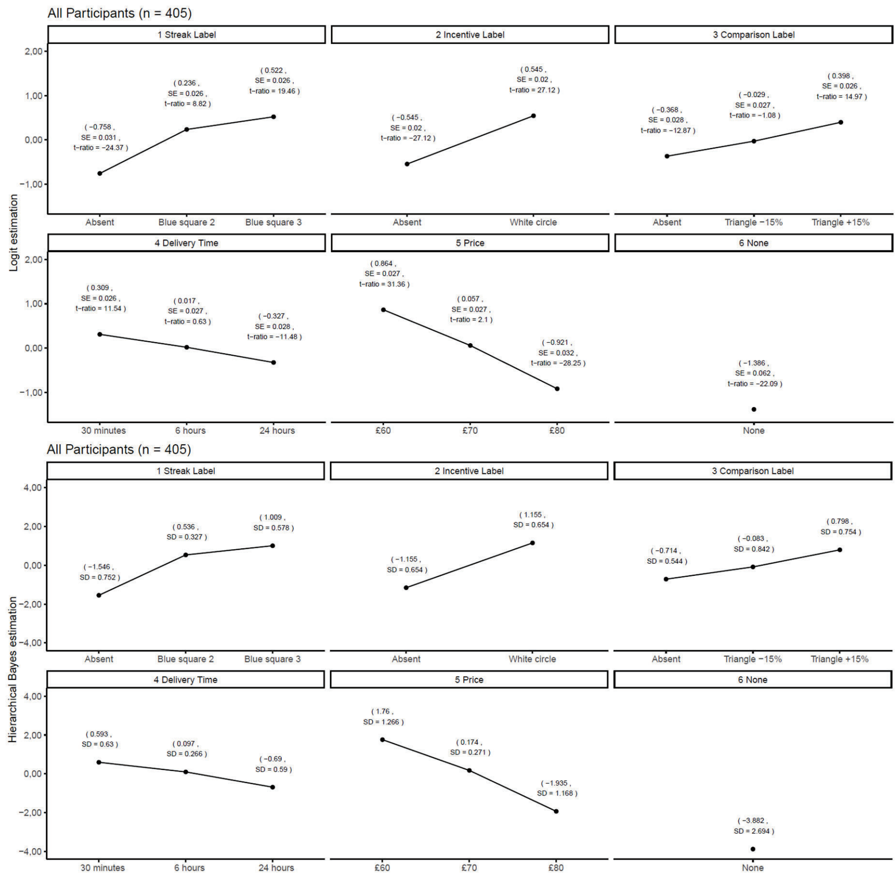

FIGURE 4
Results from estimated impact on choice on all participants. This figure shows the estimated impact of the independent variables on choice behavior. The name of the independent variables, their levels, the results of the logistic regression, and hierarchical Bayes from top to bottom.

delivery time compared to non-impulsive participants. In addition, the results in Table 1 show that impulsive and non-impulsive individuals have different preferences regarding what type of products are bought online. For instance, a higher proportion of non-impulsive participants stated that they bought products online that were in the category "Do it yourself/home improvement" than impulsive individuals. One possible explanation is that such products require more effort than other products. This can be related to previous research indicating that preference for some commodities is more impacted by the same variables that affect delay discounting.

With regard to self-monitoring of healthy food choice, the findings of this study are in accordance with articles that were used in the literature review, where self-monitoring may impact food and healthy choice. In addition, this study builds on previous calls to investigate the effects of automatic self-monitoring of previous food choice in a point-of-purchase situation which includes personal feedback. Moreover, this study also strengthens these findings by isolating the effects of self-monitoring of healthy food choice on food choice. Specifically, the results show that the presentation of higher values of healthy food choice alone can impact current food choice. Lastly, this study found that some of the effects of self-monitoring are generalizable to hypothetical online grocery shopping. With regard to pre-commitment to healthy food choice, the findings of this study support previous research in the sense that pre-commitment to healthy food choice might be an effective strategy for increasing healthy food choice. Specifically, price reductions might be effective in increasing fruit and vegetable choice, as indicated in the literature. Similarly, this effect was also observed in a hypothetical online grocery context. With regard to the social comparison of healthy food choice, the findings of this study show mixed support for previous research. This study found that positive social comparison increases food choice compared to its absence. However, the articles that were found in the literature review suggest that social comparison might have negative effects on food choice. For instance, Gonçalves et al. (62) found different

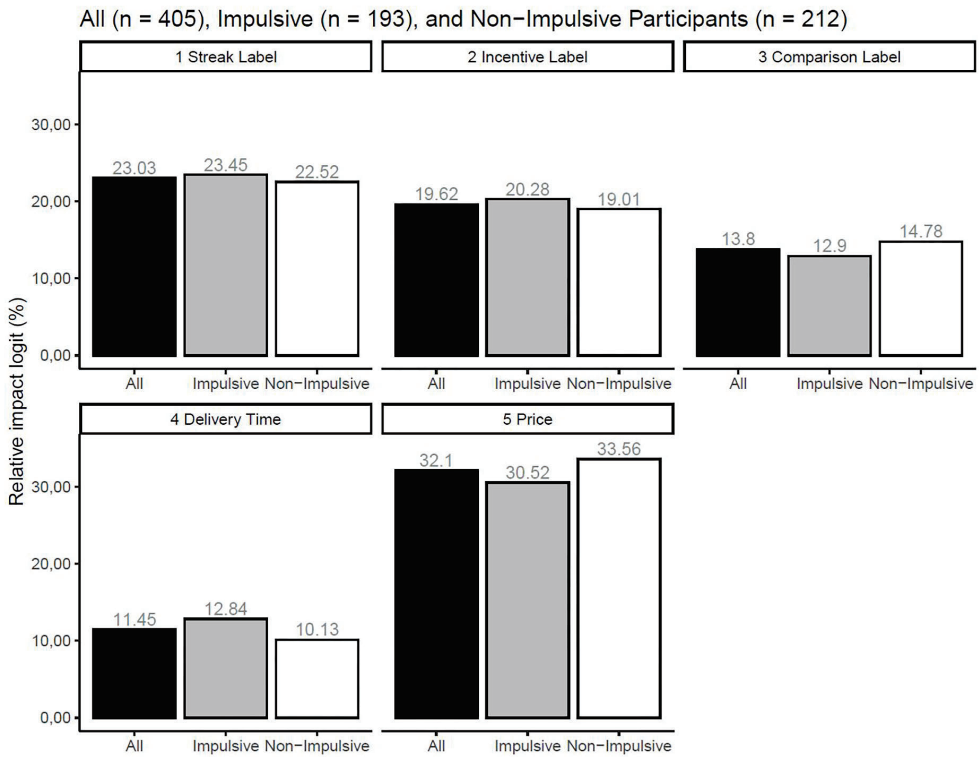

FIGURE 5
Relative impact of the independent variables for all, impulsive, and non-impulsive participants.

effects of social comparison on food choice depending on whether the participants were frequent or non-frequent fruit and vegetable buyers. The findings in this study indicate that social comparison-based technology-enabled healthy food labels were more effective for non-impulsive participants. As indicated in Table 1, more non-impulsive participants stated that they bought groceries online at least once a week compared to impulsive consumers. The results presented in Figure 5, however, suggest that frequent fruit and vegetable buyers, in this case, non-impulsive participants, were more impacted by social comparison than impulsive participants. One possible interpretation is that such buyers are more sensitive to social comparison in an online grocery store context than in a physical store.

4.3. Implications and further research

There are several implications of these findings. First, the results show that consumers' choices were more impacted by the Streak label than by Incentive labels. These finding that in some situations consumers prefer non-monetary over some discount monetary-based technology-enabled healthy food labels indicates that companies might use this technology to save costs while at the same time increase healthy food choice for consumers. Companies may use self-monitoring labels rather than providing a 10% discount on healthy foods to increase healthy food choice. Self-monitoring-based technology-enabled healthy food labels can benefit companies, consumers, and society at large. Second, developing these self-monitoring-based technology-enabled healthy food labels might not be expensive. Most online grocery stores require customers to create an account to purchase groceries. Online grocers can integrate this information into the customers' accounts, which may be presented in point-of-purchase situations. Third, several considerations must be considered when implementing new technology. For instance, privacy, accurate data, ownership, and accessibility of data being collected must be considered (68). Fourth, the findings suggest that negative social comparison-based technology-enabled healthy food labels are preferred over the absence of such labels, indicating that the negative impact of these on food choice compared to their absence is not that detrimental for food choice. Fifth, implementing such technology-enabled healthy food labels might generate more engagement with the online grocery store, which may generate positive word-of-mouth. Lastly, not only can companies that implement these technology-enabled healthy food labels generate more revenue, but they can also provide

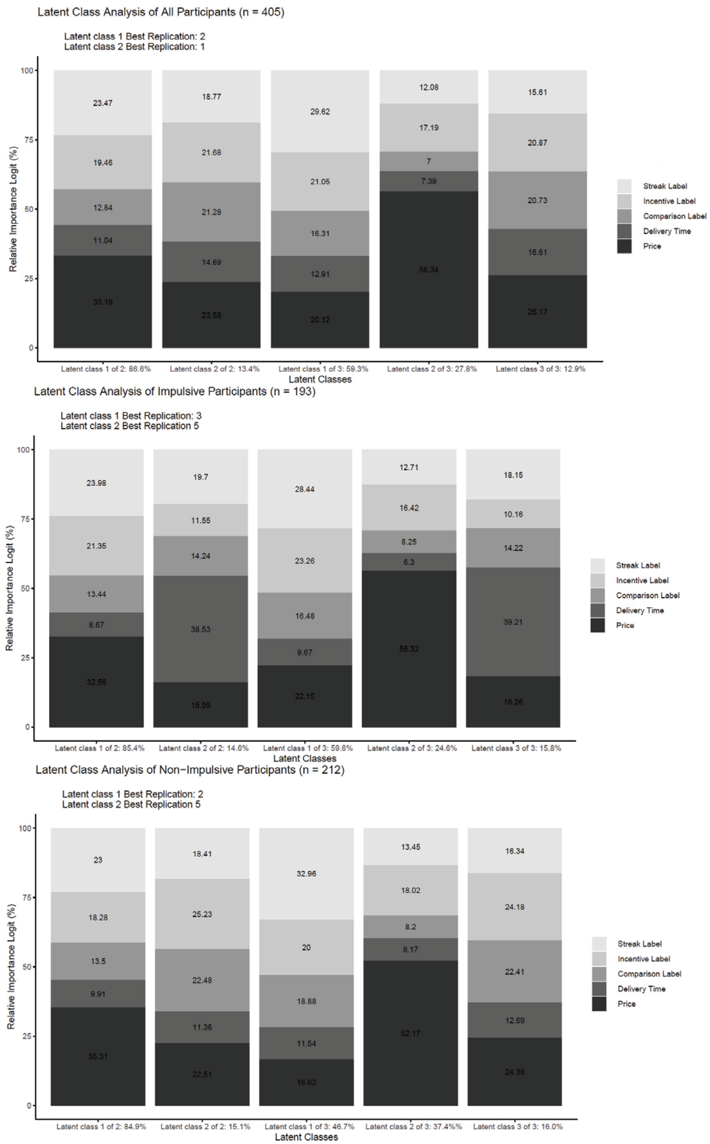

FIGURE 6
Results from latent class analysis for all, impulsive, and non-impulsive participants. This figure shows the results of the latent class analysis for all, impulsive, and non-impulsive participants.

higher consumer well-being by not restricting the consumers' product options.

There are several considerations that future studies could investigate. First, these results might be specific to UK participants, and these results might depend on cultural factors as well. Second, what was considered healthy by the Streak label and Comparison-based labels were based on the Traffic Light Food Labelling System, a front-of-package food labeling system used in the UK. The Incentive label was, however, based on how many fruits and vegetables were in the hypothetical food basket. These differences may have impacted choice behavior. However, the Comparison label was the least impactful technology-enabled healthy food label in this study, and was based on the Traffic Light Food Labeling System. Third, some order effects might have affected choice behavior. Specifically, the order of the attributes was fixed in the choice experiment, which might be a confounding variable. In addition, the sequence of the introduction to the technology-enabled healthy food labels might also have impacted the results. Fourth, this study investigated hypothetical online grocery shopping and did not investigate the effects of these technology-enabled healthy food labels on actual purchases. The findings of this study may differ in a real online purchase situation. Lastly, the sample size of the latent class analysis of three groups might be too small to give robust findings, and they should be viewed as an indication. However, the logistic and Hierarchical Bayes estimations of the relative impact of the technology-enabled healthy food labels based on all participants, impulsive participants and non-impulsive participants, had an adequate sample size as indicated by the standard errors.

Several research topics should be investigated based on the findings of this study. First, future research should investigate how these technology-enabled healthy food labels impact actual purchases of healthy foods. Second, future research should also investigate the impact of other forms of technology-enabled healthy food labels on food choice. For instance, one might present technology-enabled healthy food labels that present the benefits of selecting healthy food baskets in terms of how one increases one's life expectancy by selecting healthier options. Furthermore, one might highlight healthy foods not previously purchased at the point-of-purchase in an online grocery store to increase healthy food choice variety. In addition, many criteria exist for a healthy food product. One can ask what specific food products or categories are considered healthy for each consumer when creating an account for an online grocery store and highlight food products that are considered healthy for each consumer using technology-enabled healthy food labels. Third, this study investigated whether some technology-enabled healthy food labels were more effective for impulsive and non-impulsive consumers. Future findings may also investigate whether variables that impact probability discounting might impact healthy food choice. Specifically, some technology-enabled healthy food labels might be more effective for risky and risk-aversive consumers. As mentioned, unhealthy food consumption is associated with numerous diseases, and an increase in unhealthy food consumption increases the risk (or probability) of acquiring such diseases. Hence, variables that might impact risk-taking might be the same variables that impact healthy food choice.

Data availability statement

The datasets presented in this article are not readily available because the data that has been used in this study is confidential. Requests to access the datasets should be directed to NL, nikola.kristiania@kristiania.no.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

Author contributions

NL came up with the idea and performed data analysis. NL and AF planned the study. VS and EA provided input on data presentation and refinement of concepts. All authors contributed to the discussion of the results and final manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnut.2023.1129883/full#supplementary-material

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Attachment 3 is not published here due to copyright reasons.

What Does "Healthy" Mean, Anyway? The Impact of Public Policy, Retailer, and Consumer Self-Generated Labels on Online Grocery Shopping

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Abstract

One way to increase healthy food choices is by presenting consumers with healthy food labels that are made possible by using digital technology based on knowledge from behavioral science. Conceptually, food labels are arbitrary symbols that acquire their function on consumer behavior via instructions. This study examined how different sources of presenting such information may impact consumer behavior. It investigated the impact of technology-enabled healthy food labels made in response to public policy measures, retailers, and consumers' definitions of what a healthy food product is, on verbal reports of the likelihood of purchasing hypothetical orders by using conjoint analysis. Based on 204 adult participants, this study found that the labels that were consumer self-generated, based on public policy, and retailer-defined had the most to least relative impact on the likelihood of purchasing in that order. Furthermore, the findings also show that there were differences in which food categories public policy recommends consumers eat more of and what food categories consumers consider healthy. The study discusses the managerial implications of these findings and the practical implementation of these labels. Future research directions and possible moderating variables are discussed.

Keywords: consumer behavior analysis, online grocery shopping, healthy food labels, digital technology, technology-enabled healthy food labels

1. Introduction

Why are people choosing unhealthy food products despite their numerous negative impacts? This harms consumers, society as a whole, and retailers. From the consumers' perspective, poor nutrition is associated with numerous negative implications, such as being obese. A raised body mass index may increase the risk of cardiovascular diseases such as heart disease and stroke, diabetes, musculoskeletal disorders, and certain types of cancers (World Health Organization, 2020b). Furthermore, some research indicates an association between diet quality and academic performance (Florence et al., 2008), mental health (O'neil et al., 2014), and dental health (Mobley et al., 2009). Even when consumers intend to or state that they want to eat healthily (Grimmelt, 2022), some still continue to choose unhealthy food products. From the perspective of society as a whole, obesity is costly (Okunogbe et al., 2021) in terms of healthcare services for treating diseases. The World Health Organization has declared obesity a major public health problem and even a global epidemic. Some authors have suggested that the food environment may impact unhealthy food decisions (Lake & Townshend, 2006), which may also apply to the digital food environment (Granheim et al., 2022). This has led to several initiatives to help consumers choose healthily with various degrees of success. For instance, the World Health Organization has suggested using simplified front-of-package food labels (World Health Organization, 2020a) or simply healthy food labels as a strategy to increase healthy food choices. There is extensive research on this topic on several consumer behavior metrics (Hersey et al., 2013; Ikonen et al., 2020; Vyth et al., 2012), but some research suggests that they may not necessarily lead to an increase in healthy food purchases (An et al., 2021). From the food industry’s perspective, any company’s purpose is to satisfy consumers’ needs and wants profitably (Foxall, 1999, 2020; Foxall, 2021). Unhealthy food choices may lead to stricter regulations regarding retailing practices, limiting what products the retailers can sell. Furthermore, it may hurt the reputations of retailers and brand owners if warning labels (Reyes et al., 2019) are enforced on unhealthy food products. Moreover, consumers are becoming more sophisticated and knowledgeable about the products they need and want (Foxall, 2021). Retailers and brand owners must respond to these needs and wants. Furthermore, individuals are said to have freedom when not being threatened or punished for performing specific actions (Skinner, 1972). Retailers thus have a responsibility to ensure consumer freedom by creating a shopping environment without threats or warning labels on unhealthy food products, by not limiting their product options, by increasing consumer well-being, and by making a profit while doing so.

Retailers may increase their revenue by presenting healthy food labels based on digital technology and behavior science at the point of purchase settings. With regard to technology in retailing, Inman and Nikolova (2017) suggest that new technologies may provide value to retailers by increasing revenue through imparting better understanding of the willingness-to-pay of different consumers, by being used to increase the quantity purchased by current consumers, attracting new shoppers, and gaining support from suppliers who wish to sell more product. Similarly, Shankar et al. (2021) suggest that new technology in retail may depend on the adaptation by retailers and suppliers on one hand and customers and employees on the other hand. Furthermore, they state that retailers' decisions to use new technology may depend on what type of technology they should use, when they should implement it, the degree of investment the retailer can afford, and whether it is possible to execute this implementation. As Nikolova and Inman (2015) indicate, healthy food labels on products may increase healthy food choices and make consumers less price-sensitive and more promotion-sensitive. A healthy food label may be defined as the use of simplified nutritional information, logos, or symbols in relation to a food product to indicate that it is healthy for consumers (Hersey et al., 2013), and in the literature dealing with front-of-package food labels, they can be classified as summary labels or nutrient-specific labels (Temple, 2020) or as labels in which these elements are combined. Summary labels provide an overall evaluation of how healthy the overall food product is, nutrient-specific labels give evaluations of how healthy each nutrient is, and combined labels employ both these elements. These may be presented in novel ways by using digital technology. Using digital technology to present healthy food labels may provide new value for retailers and suppliers. With regard to digital technology in grocery shopping, there are several opportunities to increase healthy food choices (Pitts et al., 2018). For instance, one may use online grocery stores (Shin et al., 2020), mobile apps (Fagerstrøm, Eriksson, et al., 2020), and smart carts (Eriksson et al., 2023; Larsen & Sigurdsson, 2019) to present information that is otherwise not possible, using such technology. Although the potential to increase healthy food choices is made possible by using such technology, there are still uncertainties regarding what specific type of information or design one may present to the consumers (Valenčič et al., 2022). Some authors have suggested using behavioral science to increase healthy food choices (Just & Payne, 2009; Roberto &

Kawachi, 2014; Vecchio & Cavallo, 2019), and that providing detailed information regarding healthy products may not be effective in increasing healthy food choices. Hence, identifying how one can present simplified healthy food labels using technology based on behavioral science may be one way to ameliorate this problem. This has clear benefits for consumers, society, and the food industry.

There are several research gaps in the literature regarding this topic. First, there is a lack of research about presenting healthy food labels based on technology and consumer behavior. Although there exist several research articles that have investigated how healthy food labels impact consumer behavior in a digital context (Fagerstrøm et al., 2019), few articles have examined how healthy food labels in terms of arbitrary symbols enabled by technology and emphasizing the healthfulness of products may impact consumer behavior in an online grocery store context (Ljusic et al., 2022; Schruff-Lim et al., 2023; Valenčič et al., 2022). For instance, Shin et al. (2020) found that a dynamic food label with real-time feedback based on the contents of consumers' virtual baskets effectively increased healthy food purchases. Fuchs et al. (2019) found that user-specific tailored healthy food labels based on gender, age, physical activity, diet patterns, and diseases were perceived as more helpful, relevant, and recommendable than standardized healthy food labels. When it comes to food ordering in general, a series of experiments conducted by VanEpps and colleagues (2021) found that real-time feedback through a color-coding system reduces calories in orders more effectively than feedback based only on numeric calories. Second, consumers, public policy organizations, and retailers may have different definitions of what is considered a healthy food product, and this may lead to confusion regarding what a healthy food label is said to represent (Mayer et al., 1993; Spiteri Cornish & Moraes, 2015). There exists a lack of research when it comes to the impact of different sources in relation to these logos or symbols on consumer behavior in the context of information that is presented by technology. The objective of this research is to examine how different sources of healthy food label strategies may impact consumer preference. This research paper aims to contribute to research regarding these topics. The research question of this paper is thus:

What is the relative impact of (a) public policy, (b) retailer, and (c) consumer self-generated healthy food labels on verbal estimations of the likelihood to purchase of consumers in a hypothetical online grocery store context?

The rest of this paper is structured as follows. First, it introduces consumer behavior analysis as a framework within behavior science and proposes that healthy food labels acquire their function based on rules. Previous research related to public policy, retailers, and consumer self-generated instructions for healthy food products is provided. The justification for selecting these points is that the theoretical framework builds on how environmental and situational variables impact consumer behavior, that there exists some prior research on rule-following based on different sources, and that digital technologies can enable new environments for consumers, integrating these streams of research when examining technology-enabled healthy food labeling and consumer behavior. Second, the method, consisting of a conjoint experiment is described. Third, the results of the conjoint experiment are presented.

Finally, a discussion regarding the findings is provided, and future research is proposed.

2. Theoretical Framework

Consumer behavior analysis is the study of how environmental or situational variables may impact consumer behavior, its basic model is the three-term contingency, and several research articles exist on the topic. Consumer behavior analysis is an interdisciplinary approach that builds on behavior analysis, behavioral economics, and marketing science (Foxall, 2016; 2017) in order to describe, predict, influence, interpret, and understand the behaviors of consumers. The three-term contingency describes the relationship between behavior, consequences, and antecedent stimuli. The behavior-consequence relations may be described in terms of reinforcement and punishment and related to utilitarian and informational properties of such consequences. The antecedent-behavior-consequence relations, that is, the full three-term contingency, may be analyzed by introducing discriminative stimuli and motivating operations. Reinforcement, as a process, refers to where environmental consequences of behavior increase behavior, while punishment is where environmental consequences decrease behavior (Catania, 2013). Utilitarian consequences are consequences related to owning or using the product or service, while informational consequences are consequences given by other people (Foxall, 2017), such as friends and family. Antecedent events may be discriminative stimuli or motivating operations. A discriminative stimulus signals the availability of behavior-consequence relations (Dinsmoor, 1995). Motivating operations are events that have a value-altering effect on consequences or a behavior-altering effect on behaviors that have produced such consequences (Langthorne & McGill, 2009; Michael, 1982). Establishing operations are events that increase the effect of the consequences or evoke behaviors that have produced such consequences, while abolishing operations are events that decrease such consequences or abate behavior that has produced them. For instance, giving money to the cashier when purchasing food items may be maintained by gaining access to consuming a healthy product (utilitarian reinforcement). Furthermore, a healthy food label may signal that the relationship between giving money and gaining access to healthy products holds in the presence of such labels (discriminative stimulus). In addition, going a long period without eating healthy food may increase the value of gaining access to healthy products and may increase behavior that has produced such consequences before (establishing operations).

This model has been used to investigate different phenomena related to consumer behavior. For instance, research exists on the motivating effects of antecedent stimuli in webshops on the likelihood to purchase (Fagerstrøm, 2010), on utilitarian and informational reinforcers from the marketer related to co-value creation and their impact on verbal reports of the likelihood to share the idea with the company (Fagerstrøm, Bendheim, et al., 2020), and on utilitarian and informational consequences in terms of e-mail marketing related to the purchase of books (Sigurdsson et al., 2013). Furthermore, several authors have suggested that future research should aim to use the concept of rule-governed behavior in consumer behavior research (Wells, 2014) because much of human behavior occurs in a social context.

Rule-governed behavior can be defined as behavior that is under the influence of rules or contingency-specifying stimuli (Skinner, 1969). Rules or instructions are verbal antecedent stimuli that describe the contingency between the behavior and its consequences and antecedent stimuli. In the behavior-analytic literature, behavior may be directly influenced by the consequences or antecedent events of behavior, or behavior may be under the indirect control of these environmental events through instructions or rules. Such rules have a function-altering effect (Schlinger & Blakely, 1987), meaning that environmental events may be altered as a function of such rules. For instance, the consumer may encounter this text: “Look for the healthy food label when you are at Tesco and buy such products. They are healthy.” Such text may now change how these labels impact consumer behavior, as they may act as discriminative stimuli, motivating operations, or other antecedent stimuli.

There are several types of rules. For instance, Zettle and Hayes (1982) suggest that rules may be described as tracks, plys, and augmentals. Tracks are rules that influence rule-governed behavior because of the correspondence between following the rule and the existing environmental contingencies. Plys do this where rule-following is socially mediated by the rule-giver. Lastly, augumentals do this by altering existing or previously neutral consequences to function as reinforcers or punishers. Following the previous example, the instruction may function as a track if buying is maintained by the consequences described in the rule. Consumers may follow it as a ply due to a family member delivering the statement, not due to the consequence that is described in the rule. They may also follow this statement because such a statement increases the value and behaviors related to gaining access to healthy products. Some authors have noted that these terms may lack precision regarding experimental analysis of behavior (Kissi et al., 2017). However, they may be useful as middle-level terms rather than technical terms (Harte & Barnes-Holmes, 2021). Another taxonomy for rules was proposed by Pelaez and Moreno (1998). They suggest that rules may have different degrees of (a) explicitness in the sense that they describe the full behavior, consequences, and antecedent relation or only parts of these, (b) accuracy in that the rule indeed describes future events correctly or not, (c) complexity in that the environmental stimuli that are described consist of one or many dimensions, and (d) source in that rules may be provided by others or by the individual themselves. The rule “Look for the healthy food label when you are at Tesco and buy such products. They are healthy.” is a full statement, may be accurate for that store and consumer needs, and is complex in that it describes multiple antecedent stimuli such as a label and a store, and that the source of the rule may b a family member and prior history of rule-following of that source will impact whether the rule will be followed.

There are some articles on rule-governed behavior within consumer behavior analysis (see Fagerstrøm et al., 2010 for a conceptual overview). For instance, Fagerstrøm et al. (2015) investigated how corporate social responsibility statements, conceptualized as a rule, combined with product quality, product wash, brand, and price, impacted verbal reports of the likelihood of purchasing workout clothes. They found that price, brand, product wash, corporate social responsibility, and product quality had the most to least influence on the likelihood of purchasing workout clothes in that order. Similarly, Eriksson and Fagerstrøm (2018) used a conjoint experiment to examine the impact of Wi-Fi review, Wi-Fi price, hotel rating, brand, and price per night on verbal reports of the likelihood of booking hotel rooms. Wi-Fi review and Wi-Fi price were conceptualized as rules in that study. They found that hotel rating, price per night, Wi-Fi review, and Wi-Fi price had the most to least impact on the likelihood of booking a hotel in that order. In addition, Fagerstrøm et al. (2021) tested an up-sell offer related to either product improvement or a lower price offer in an online business-to-business retail experiment in a natural setting. They conceptualized such up-sell offers as augmentals and found that the conversion rate was 39% and revenue increased by 87.94% compared to a control group. However, although there exists literature on self-generated rules in general (Barnes-Holmes et al., 2001; Hayes et al., 1989) and it has been mentioned in relation to consumer behavior analysis (Fagerstrøm & Arntzen, 2013; Fagerstrøm et al., 2011; Foxall & Sigurdsson, 2013), few empirical articles exist on different sources of rule-givers in the context of consumer behavior and their impact on healthy food behavior.

In the context of healthy food promoted by public policy measures, such as front-of-package food labels, some research has suggested that they may increase healthy food choices to some degree (Finkelstein et al., 2021; Fuchs et al., 2022; Michels et al., 2023; Shin et al., 2020). For instance, Fuchs et al. (2022) conducted a randomized controlled trial on the nutritional quality of an individual’s weekly grocery shopping as a function of a Chrome web browser extension that presented digital food labels on food products. They briefly described what the healthy food label system does, among other attributes of the shop. They found that participants presented with such labels had, on average, higher nutritional quality than controls. Finkelstein et al. (2021) conducted a study to investigate the impact of front-of-package food labels alone, in combination with a physical activity equivalent label, and the absence of such labels on online grocery shopping. They also presented instructions on what the physical activity equivalent label shows. They found that participants presented with the front-of-package labels purchased, on average, a larger proportion of products with those labels compared to the control group. However, no differences were found in the number of calories per serving purchased, meaning that such labels do not necessarily lead to healthier overall purchases. These studies indicate that public policy healthy food labels in an online grocery store may increase the likelihood of purchasing compared to the absence of such labels.

In the context of healthy food promotion by the retailer in an online grocery store setting, some literature indicates that the retailer's promotion of healthy food has a mixed impact on increasing healthy food choices (Bunten et al., 2022; Sigurdsson, Larsen, Alemu, et al., 2020; Zou & Liu, 2019). For instance, Zou and Liu (2019) examined the impact of nutrition information on the interactional effects between this information and the seller's reputation in relation to healthy and unhealthy food products in online grocery stores. They found that nutrition information increases food sales, that seller reputation can moderate the influence of this information, and that such information is more effective in increasing healthy products than unhealthy products. Sigurdsson et al. (2020) conducted three studies on variables that may increase fresh fish sales. In study 1, they investigated the impact of other consumers' product rating, procurement method, country of origin, price, delivery, purchase state, and item signage on hypothetical online grocery shopping. Their results show that these variables had the most to least impact on choice behavior in that order. Regarding signage, their results show that "store's choice" information had a higher estimated impact than no signage. In contrast, Bunten et al. (2022) conducted a study examining the influence of advertisement banners and ingredient lists of healthier food products on purchases of such food products. They stated that there was little evidence showing that healthier products combined with such banners led to the purchase of healthier food products. These studies indicate that the presence of retailers' healthy food labels in an online grocery store may increase the likelihood of purchasing compared to the absence of such labels.

Several articles have examined the effect of self-generated rules on rule-following in controlled settings and have found that rule-following occurs when participants have the chance to form their own rules (e.g., Baumann et al., 2009; Harte et al., 2017; Rosenfarb et al., 1992). However, few articles have investigated how self-generation of rules may occur when defining which products are healthy, such as healthy food labeling made possible by the use of digital technology and its impact consumer preferences. Some research exists on how consumer preference may be changed by introducing interventions that the consumer may impose on themselves through the use of digital technology (Michels et al., 2023; Shin et al., 2020) and what food products consumers consider healthy (Lusk, 2019). For instance, Michels et al. (2023) investigated the effects of reducing color intensity on unhealthy food products on the choice of products that have healthy food labels and how participants' choice is moderated by presetting and self-imposing such color reduction. The study gave some participants instructions that specified the relationship between selecting unhealthy food products and their health consequences. They found that participants who were presented with a color reduction of unhealthy food had fewer unhealthy food choices. Furthermore, they found that participants in the self-imposing condition with the rule influenced the selection of unhealthy food products. Furthermore, Shin et al. (2020) investigated the effects of seven dynamic food labels compared to their absence on grocery purchases in an online grocery store setting. A pop-up window presented instructions on how to use these dynamic labels. The participants could choose which of the seven types of information they would be displayed for. They found that the diet quality of the purchases was higher for participants who were presented with the label than purchases for participants who were not presented with such labels. However, these studies did not examine in combination what the individual consumer views as healthy food products and how labels based on this impact consumer preference. Furthermore, these studies have combined whether participants would like to be presented with a healthy food labeling system created by established food labeling systems through public policy sources. The results might be different if the consumers were to define what products they consider to be healthy. The majority of the studies mentioned here on self-generated rules (Baumann et al., 2009; Harte et al., 2017; Rosenfarb et al., 1992) and some studies related to giving consumers the option to impose strategies on themselves (Michels et al., 2023; Shin et al., 2020) indicate that these strategies may impact rule-following or choice of healthy food products. Based on these studies, one may expect that when consumers are given the option to define which products they consider healthy, such information may increase the likelihood of purchasing compared to its absence.

3. Material and Methods

3.1 Participants

A total of 216 participants from Prolific.co were invited to participate in the current study, and 204 participants completed it. The sample consisted of a balanced sample of males and females in the United Kingdom. They were told that the purpose of the study was to investigate consumer behavior in a hypothetical online grocery store context, that they would receive £9 per hour, and that the study would take approximately 13 minutes to complete. They were required to read and confirm an informed consent form regarding their rights as research participants prior to their participation, and they could end their participation at any time. No personally identifiable questions were asked. This study was approved by the Norwegian Agency for Shared Services in Education and Research (Ref. No. 837021).

3.2 Setting, apparatus, and materials

This study took place in an online computer setting. First, Sawtooth Software Lighthouse Studio 9.14.2 was used to present the procedure and record participants' responses. Second, Prolific.co was used to recruit participants. Lastly, Excel and R with the conjoint package were used for producing the experimental design in the conjoint experiment, and MASS, olsrr, limtest, ggplot2, and other packages were used for data analysis and visualization.

3.3 Procedure

A pilot study consisting of 98 participants was undertaken. The current study was updated to rule out grammar mistakes and confounding variables, make changes to the procedure, update the list regarding food items, and add new questions regarding consumer habits. Furthermore, the participants from the pilot study were not invited to participate in this study, and their responses were not used in the analysis of this study.

The first phase consisted of presenting the following text: *Imagine that you are doing some online grocery shopping. You selected the products you wanted. You notice that the online grocery store has different healthy food labels based on your virtual basket: Traffic-Light Healthy Bar, Store's Healthy Bar, and Your Healthy Bar. You decide to investigate what these labels mean. Press "Next" to continue.*

The second phase introduced information related to public policy, retailers, and self-generated healthy food labels in random order. For the public policy healthy food label, an empty blue bar with a zero-percentage sign above it was presented with this instruction: *This is the Traffic-Light Healthy Food Label Bar.* Participants had to press next, and this extended information was presented underneath the bar: *This label shows how many products in your basket are labelled healthy by the Traffic Light Food Labelling System. Specifically, it shows the percentage of products with at least one green nutrient. Press "Next" to continue.* Later, the participants were presented with a picture of this label and with the three text options (one of which was identical to the text described above) and were asked what the label does. They were reintroduced to the label if they selected options other than the one described above. They continued if they selected the text identical to the one above. For the retailer's healthy food label, an empty purple bar with a zero-percentage sign above it and with the following instructions was presented*: This is the Store's Healthy Food Label Bar*. Similarly, participants had to press next, and this extended information was presented underneath the bar: *This label shows how many products in your basket are labelled healthy by the store. Specifically, it shows the percentage of products labelled healthy by the online grocery store. Press "Next" to continue*. Similarly, they had to select the one identical to the instruction above to continue, or they were reintroduced to the label if they selected the other options. For the self-generated healthy food label, an empty indigo bar with a zero-percentage sign above it and with the following instructions was presented: *This is Your Healthy Food Label Bar*. Similarly, participants had to press next, and this extended information was presented: *This label shows how many products in your basket are labelled healthy by your standards. Specifically, it shows the percentage of products labelled healthy based on your perception of what healthy is. Press "Next" to continue.* Similarly, they had to select the one identical to the instruction above to continue, or they were reintroduced to the label if they selected any of the other options. Participants were later presented with a list of different food products and the following instructions: *Select which products you consider healthy for Your Healthy Bar.* They were required to select at least 10 products from the list to proceed. The list consisted of 90 products derived from six food categories by the Eatwell Guide (Public Health England 2018): (a) fruit and vegetables; (b) potatoes, bread, rice, pasta, and other starchy carbohydrates; (c) dairy and dairy alternatives; (d) beans, pulses, fish, eggs, meat, and other proteins; (e) oils and spreads; and (f) foods to eat less often and in small amounts. There were 15 products per food category; all items were presented in random order, and the participants were required to select at least 10 items in that list in order to proceed.

The third phase consisted of a conjoint experiment. Conjoint experiments allow for decompositional models to identify which product characteristic has the most impact on consumer behavior (Hair et al., 2014). Participants were presented with the following information before the conjoint experiment: *You are now done with phase 1 and will start phase 2. You have added your products to your virtual basket and are now at the checkout of an online grocery store. You will now be presented with a series of hypothetical purchase scenarios. These scenarios are independent of each other, and your answer in one scenario does not impact the next.* This study used a single concept profile and full-profile method; 16 profiles were presented to the participants, and one experimental design was generated. A fractional factorial design was used, and the levels of the independent variables were generated by using the conjoint package in R. When presented with a profile, participants were presented with this instruction: *This virtual basket has the following information* and *Moving your mouse cursor over "more info" gives you extended information. On a scale from 1 (Definitely Would Not Purchase) to 7 (Definitely Would Purchase), how likely are you to purchase this order?* Hovering the mouse cursor over each label resulted in a presentation of the text for each label described in the second phase.

The experimental design consisted of 16 profiles, which are shown in Table 1. Each profile was presented to the participants in random order, and an example trial is shown in Figure 1. The independent variables for this study were public policy labels, retailer labels, self-generated labels, delivery time, and price. The public policy label had a bar that was 70% full, a bar that was 30% full, or an absence of such labels. The retailer label had a bar that was 70% full, a bar that was 30% full, or an absence of such labels. The self-generated label had a bar that was 70% full, a bar that was 30% full, or an absence of such labels. The delivery time had these levels: 30 minutes, Next day, and In two days. The price variable had the following levels: £60, £70, and £80. The last two independent variables were added to increase realism in the conjoint experiment. The dependent variable in this study was participants' preference in terms of verbal reports regarding the likelihood of purchasing these hypothetical products on a 7-point scale. Finally, 15 questions regarding consumer habits were asked. Participants who stated that they had never ordered groceries online in question 1 were later only presented with questions numbered 3, 9, 10, 13, and 15.

3.4 Data analysis

Several analyses were performed, including data analysis related to the relationship between variables, regression diagnostics, the relative importance of each independent variable, what food products the participant selected to count as healthy, and answers regarding consumer habits. First, multiple regression analysis with main effects was performed using levels as categorical predictor variables, and the outcome variable was the aggregated likelihood to purchase. A dummy coding approach consisted of 0 for the absence and 1 for the presence of levels. The last level in an independent variable was used as a reference category. The estimates, standard error, t-value, and p-value were reported for each level. For the overall model, multiple R^2, adjusted R^2, F-statistic, and p-value of the model were used to examine the relationships between variables. Normality, linearity, homoscedasticity, multi-collinearity, and influential data points were assessed. Normality was assessed by using a histogram of the frequency of residuals of the model, a Q-Q plot, and a Shapiro-Wilk normality test. Linearity was assessed by plotting residuals of the model across estimated values and by using a Ramsey Regression Equation Specification Error Test (RESET). Homoscedasticity was assessed by plotting the square root of standardized residuals across estimates of the model and by using a non-constant variance score test. Multi-collinearity was assessed by using a generalized variance inflator factor test. Influential data points were assessed by using Cook's distance, DIFFITS, and DFBETAS. Second, the relative importance of each independent variable was presented (Orme, 2020). Finally, the participants selected which food products were healthy, and questions regarding consumer habits were presented. The dataset that contains each observation, the regression diagnostics, and the R script is presented in Supplementary Material.

4. Results

Out of the 216 participants who were invited, 204 participants completed the study. The mean time to completion was 10.35 minutes, the median was 9.12 minutes, the standard deviation was 5.075 minutes, and the fastest and slowest participant took 3.45 and 43.55 minutes, respectively.

The result of the multiple regression analysis is shown in Table 2. The regression results show that verbal reports of the likelihood to purchase when in the presence of the Traffic-Light Healthy Bar (TLHB) with 70% full was estimated higher compared to the absence of such a label (the reference category), and that the estimates were lower when in the presence of TLHB with a bar showing 30% compared to its absence. Similar findings were found for the Store's Healthy Bar (SHB) and Your Healthy Bar (YHB). Furthermore, the results show estimates of verbal reports of likelihood to purchase were higher in the presence of "30 minutes" and "Next day" compared to "In two days" (the reference category). Lastly, estimates of verbal reports of the likelihood to purchase were higher in the presence of £60 and £70 compared to estimates of £80. The lowest standard error of the estimates was 0.0243, and the highest was 0.0383. All of the estimates were statistically significant except for estimates from the £60 predictor.

The overall model had a multiple R^2 of 32.36%, adjusted R^2 was 32.15%, and the F-statistic was 115.6 with a p-value of less than 0.05. Normality assumptions are mixed, as the histogram of the frequency of residuals of the model (SA Figure 1) indicates some characteristics of a normal distribution by visual inspection, the Q-Q plot indicates normal distribution by visual inspection (SA Figure 2.), the Shapiro-Wilk normality test had a value of 0.9937 with a p-value of less than 0.05 (which does not indicate normality), and the skewness of the residuals was -0.009. Linearity assumptions were met as the residuals across estimated values indicate linearity (SA Figure 3), and the RESET had a value of 2.652 with a p-value of 0.070, which indicates linearity. Homoscedasticity assumptions are mixed as the squared root of standardized residuals across fitted values indicates homoscedasticity (SA Figure 4) by visual inspection and the non-constant variance score test was 43.33 and had a p-value less than 0.05, which does not indicate homoscedasticity. Multi-collinearity assumptions were met as the generalized variance inflation factor results for the independent variables are close to 1.0, which indicates a lack of multi-collinearity, as shown in SA Table 1. Influential data points were observed affecting the overall model as several data points surpassed the threshold of 0.001 in Cook’s distance (SA Figure 5) and several data points surpassed the threshold of 0.12 in DFFITS (SA Figure 6). Influential points affecting the coefficients were also observed where several data points surpassed the threshold of 0.04 in DFBETAS (SA Figure 7).

The relative importance score shows that YHB, TLHB, and SHB had the most to least relative impact on verbal reports of likelihood to purchase in that order, as shown in Figure 2. The relative importance scores were derived by finding the variability range of estimates within an independent variable for all independent variables, summing these variability ranges, and then each relative impact score for each independent variable was calculated based on the variability range of the independent variable under investigation divided by the sum of all variability ranges of the independent variables.

The food products that were selected as healthy by the participants are presented in Figure 3. Based on the food categories, fruit and vegetable food items were considered the healthiest based on the mean of food products that were selected. In second place, the averages of food items that were selected to be healthy based on food categories were beans, pulses, fish, eggs, meat, and other proteins. In third place, potatoes, bread, rice, pasta, and other starchy carbohydrates were selected as healthy. In fourth place, dairy and dairy alternatives were selected to be healthy. In fifth place, oils and spreads were considered to be healthy. In the last place, foods to eat less often and in small amounts were selected. The food product that the majority of the participants considered healthy is carrots, and the least healthy is American muffins. Within the fruit and vegetable category, the mean number of items that were selected to be healthy across all items based on all participants was 169.06, with carrots being the most selected and kiwis the least selected. Within the potatoes, bread, rice, pasta, and other starchy carbohydrates category, the mean was 73.13, with oats being the most selected and white bread being the least selected. Within dairy and dairy alternatives, the mean was 59.93, with natural yoghurt being the most and blue cheese being the least selected. Within the beans, pulses, fish, eggs, meat, and other proteins category, the mean was 108.45, with eggs being the most selected and bacon being the least selected. Within the oils and spreads category, the mean was 56.26, with olive oil being the most and ketchup being the least selected. Within the foods to eat less often and in small amounts category, the mean was 13, with honey being the most and American muffins being selected the least.

The answers from the consumer habit questions are shown in Table 3. The majority of the consumers self-reported that they order groceries online at least once a month, that they have not seen other healthy food labels that are made possible by the use of technology, that they manage to find products when ordering from online grocery stores, and that the delivery time is not too long. Furthermore, the majority stated that they do not think that there are too many online grocery stores to choose from, they prefer to use physical stores, their initial reaction to these labels in an actual online grocery store is positive, and they find healthy food labels helpful. When it comes to the rest of the questions, the majority of the participants answered, “To some extent.”

5. Discussion

This study investigated the impact of three healthy food labels enabled by technology from different sources. Specifically, this study investigated how technology-enabled healthy food labels that are based on public policy, retailers, and the individual consumers making the orders themselves may impact verbal estimations of the likelihood of purchasing products in a hypothetical online grocery store context. This study contributes to the literature regarding how simplified information that is made possible by using digital technology may influence healthy food preferences. In addition, this study investigated how different rules or instructions related to those sources may alter healthy food labels that are otherwise arbitrary logos or symbols and the relative impact of such labels on consumer behavior. To the best of our knowledge, this is the first study to do so.

These results show that the consumer self-generated, public policy, and retailer technology-enabled healthy food label had the most to least relative importance for verbal reports related to the likelihood of purchasing online grocery orders in that sequence. A technology-enabled, healthy food label bar, based on the products in the virtual basket and that had a 70% symbol was associated with higher preference compared to its absence. Moreover, the results show that such labels with a 30% symbol were associated with less preference compared to its absence. These findings applied to all three labels. Moreover, this study found that there may be a mismatch between which food products are counted as healthy food in public policy guidelines and which are deemed as healthy food products by consumers. Specifically, this study used six food categories based on the Eatwell Guide, which recommends that products within some categories be consumed more than others. This study found that products belonging to the beans, pulses, fish, eggs, meat, and other proteins category were considered healthier on average than potatoes, bread, rice, pasta, and other starchy carbohydrates. The latter category is recommended to be eaten more often than the former by the Eatwell Guide. Lastly, more participants in this study stated that they either do look for healthy food labels when doing grocery shopping compared to not looking for such labels, that they prefer to use physical stores or both physical and online stores, and that their initial reaction if they saw one of these labels in an actual online grocery store would be positive.

In relation to the literature, this study examined how rules or instructions impacted three different healthy food labels that were otherwise arbitrary logos or symbols enabled by technology. The rules in this study were the textual explanations of what the label did or was said to represent. These rules were contingency-specifying stimuli that altered antecedent stimuli, which were the arbitrary healthy food label bars. The rules in this study were partial rules in that they did not describe the consequences of purchasing such products, complex in the sense that they describe several relations between antecedent stimuli, such as the bar being in relation to the percentage sign and several products, and the rules were given by different sources. Another point is worth mentioning. The literature points to the presence of such labels generally increasing consumer preference related to food products. Although that may be the case, there may also be particularities in how the overall basket consisting of items with these labels is presented to the consumers. As indicated by the results in this study, a healthy food label bar with a higher percentage was associated with higher preference compared to its absence, but a lower percentage was associated with less preference compared to its absence. Even when labeling practices are enforced by public policy measures, by third-party certification, or implemented by the store itself, they may influence the consumers not to purchase products if they are below a certain threshold. The findings of this study in the context of previous literature must be interpreted with this in mind.

In the context of healthy food promoted by public policy measures, the findings of this study are, to some degree, consistent with the findings from the literature. In this sense, the label in this study highlighted only healthy and not unhealthy products. Furthermore, Fuchs (2022) found that a Chrome web browser extension that presented digital food labels on individual products was associated with a higher choice of products with higher nutritional quality on average compared to the control group. In addition, Finkelstein (2021) found that adding a healthy food label in terms of how healthy the overall product was or in combination with physical activity labels increased the purchase of such products on average compared to the absence of such labels. Overall, these findings are consistent with the findings of this study, as the presence of a public policy-based technology-enabled healthy food label is associated with higher preference compared to its absence.

In the context of healthy food promoted by the retailer, the findings of this study are, to some degree, consistent with findings from the literature.

Zou and Liu (2019) found that nutritional information may increase food sales in online grocery stores, that the seller's reputation can moderate such relations, and that such information may increase sales of healthier foods. This study found that healthy food labels defined by the store increased preference on average when the entire basket was healthy compared to its absence. However, the seller's reputation was not taken into consideration in this study. Furthermore, Sigurdsson et al. (2020) found that item signage consisting of "Store's Choice" was associated with a higher choice of salmon compared to a "Top Seller" and the absence of such signage in a hypothetical online grocery store setting in study 1. In study 2, they found "Top Seller" to be more impactful and "Store's Choice" to be less impactful on choice than the absence of item signage in a hypothetical physical store. In study 3, they found that relative sales of products were higher in the presence of a "Store's Choice" and "Top Seller" compared to their absence in an in-store setting. Lastly, Bunten et al. (2022) conducted an experiment where one group of customers saw advertisement banners and recipe ingredient lists that had healthier products than the other control group. They found that promotions based on healthier or standard products did not differ. This current study builds on this research and suggests that the promotion of healthy food by the store, presented through the use of digital technology, is at least associated with higher preference compared to its absence. Overall, these findings are consistent with the findings of this study, as the presence of a retailer-based technology-enabled healthy food label was associated with higher preference compared to its absence.

In the context of healthy food that is defined by the consumer who makes the order, this study's findings are, to some degree, consistent with the literature on self-generated rules and the self-imposing of healthy food interventions. In general, the results of this study are similar to studies in relation to the self-generation of rules and rule-following, as participants tend to emit behaviors that are consistent with the self-generation of rules compared to their absence (Baumann et al., 2009; Harte et al., 2017; Rosenfarb et al., 1992). When it comes to interventions that allow self-imposing interventions to promote healthy food choices, the results of this study are, to some degree, consistent with previous studies. For instance, this study shows some similarities with the study conducted by Michels et al. (2023) in the sense that healthy food labeling increases healthy food choices. However, it is worthwhile to mention that they found such effects to be statistically significant when investigating the reduction of unhealthy food choices, while the increase in healthy food choices as a function of self-imposing intervention had the lowest p-value compared to healthy food choices estimated by providing the rule. Furthermore, this study indicates similar results to those of Shin et al. (2020). They found that participants who were presented with the label made more purchases of products with diet quality and less sugar and sodium than those who were not presented with such. Similarly, this study found that a higher degree of products that the consumers consider healthy when presented by healthy food labels impacted the likelihood of purchasing than did lower levels. Overall, this study found that the presence of labels that encouraged the participants to define what they consider healthy food products impacted preference to a higher degree than labels that were in relation to rules that described how healthy the virtual basket was based on public policy or retailers' rules.

There are several alternative explanations that can shed some light on these results. First, delivery time and price had a low relative impact score compared to the technology-enabled healthy food labels. These findings may occur due to the scenario that was presented at the start of the conjoint experiment. The scenario consisted of the participants imagining that they were to do online grocery shopping, that they had selected the products that they wanted, and that they were at the checkout of the store. One possible explanation is that the consumers may have already taken the delivery time and price into consideration when adding their products to the basket, and not that the participants are insensitive to those variables in real purchase situations. Second, there exists little academic research investigating how arbitrary logos or symbols made possible by digital technology acquire their function on consumer behavior, but some participants indicated that they had seen such labels in actual online grocery stores. Lastly, although this study investigated how technology-enabled healthy food labels based on self-generated rules by consumers impact verbal reports of likelihood to purchase, it is worthwhile to mention that the rule that altered the arbitrary bar of the virtual basket had both components of rules given by the store and self-generated rules. The rule for self-generated healthy food labels specifically asked participants to show how many products in the basket they considered healthy based on their perception of what healthy food products were. In this sense, their choices were under the influence of the rule that described how the label works and under consumers' self-generated rules when they were asked to evaluate what they consider to be healthy food products.

The findings of this study must be considered in relation to its limitations. First, this study presented hypothetical profiles and used verbal estimations of the likelihood of purchasing, and this may not be directly generalized to actual purchases, although it can give some indication. Second, although the study had a balanced percentage of males and females, this was not checked directly, and this study asked minimal socio-demographical questions. Third, these results may be particular to using Prolific.co in the United Kingdom as a sample and may not generalize to other populations. Fourth, the store's healthy food label bar did not refer to any specific store, as consumers may react differently to different stores. Finally, the introduction of the technology-enabled healthy food labels started out with a zero-percentage reference point, and this study did not control for reference effects.

These findings raise several managerial implications. In particular, it raises implications for the use of technology-enabled healthy food labels where the consumers themselves may be given the choice to define what products they consider to be healthy. First, such labels may be more effective in increasing product preference compared to using healthy food labels based on public policy measures such as the traffic-light food labeling system or based on what the store considers healthy foods. Implementing these labels into online grocery stores may increase preference for such products. Second, online grocery stores may, to some degree, combine healthy food labeling based on which products the consumers consider to be healthy with the promotion of specific products.

Presenting a list of all possible products or product categories may require too much response effort for the consumers. The store may select a subset of items that it wants to promote and ask participants which of these products they consider to be healthy. A consumer may then be presented with a bar indicating the percentage of products that have these characteristics at checkout. In addition, an online grocery store may decide not to give the consumers the option to select unhealthy food products by, for instance, not allowing them to select products such as "doughnuts," "ice cream," or "chocolate." Allowing for certain items to be regarded as healthy when they are not may backfire. One solution to this is to introduce the option to select some unhealthy food products up to some criteria. This would be reasonable considering that a healthy diet consists of several products that are consumed over time, and a healthy diet does not equate to only consuming healthy individual products. Moreover, online grocery stores may use this information to identify consumers' wants and needs related to healthy food products. Similar to promotion, the online grocery store can also combine healthy food labeling based on which products the consumer considers to be healthy with some food that is considered healthy by other sources. For instance, one may present a list of healthy food products that are defined as healthy according to public policy measures, present the list to the consumers, and ask them to select which ones they consider healthy. This may also be used based on a list of food products that other consumers think are healthy. Lastly, the online grocery store may decide to only present such labels when consumers have reached a minimum score based on how healthy the virtual basket is. This may decrease the aversive events related to shopping for healthy food products and may make grocery shopping more pleasant.

This research provides several opportunities for future work within healthy food labels that are made possible by using digital technology. First, this study found that a technology-enabled healthy food label bar based on the virtual basket and that has a 70% symbol is preferred in the absence of such information. However, the order was less preferred if it had 30% compared to the absence of such information. Future research could examine what values cause consumers to be indifferent to purchasing such a product. Second, it may be the case that the individual consumer may consider that a food product is healthy at one point in time and not at another point in time. One further research direction is to examine how often a consumer may be allowed to change their definitions of what products they consider to be healthy. That is, one may investigate how (a) the possibility of updating what products they consider to be healthy moderates (b) the effectiveness of such labels on (c) consumer behavior. The possibility of updating their definitions can be set at different minimum time intervals, such as after every 24 hours, a week, a month, and four months after the consumers have defined their healthy foods. This may change the effectiveness of these labels. Another research direction would be to investigate whether consumers will continue to choose the products that they have chosen in the past when the food products are no longer considered healthy. Furthermore, the self-generated labels and their impact on consumer preference could be investigated in relation to topics on autonomy (Skinner, 1972), consumer engagement (Sigurdsson, Larsen, Sigfusdottir, et al., 2020), and ownership (Foxall, 2017). First, whether these labels ensure autonomy in reducing aversive events, such as warning labels, could be investigated. Second, these labels could influence what consumers think, do, and feel about brands, and this could be explored.

Lastly, obtaining products that promote health is an aspect related to owning and using the product. Hence, research on whether these labels better function as discriminative stimuli for utilitarian reinforcement than other labeling systems could be investigated.

6. Conclusions

This study investigated the impact of healthy food labels made possible by using digital technology on consumer preference. Specifically, this study investigated technology-enabled healthy food labels' impact on verbal reports of the likelihood of purchasing hypothetical grocery orders using online grocery stores. It did so by investigating three different sources of what counts as healthy products on consumer preference. The results show that consumer self-generated, public policy, and retailers' definitions of healthy products had the most to least relative impact on consumer preference in that order. Furthermore, the results show that consumers view food products high in protein as more healthy than starchy carbohydrates, which indicates a difference between what public policy measures recommends consumers to eat more of and what consumers consider healthy foods. In addition, most consumers stated that they would react positively if they saw these technology-enabled labels in a real online grocery store setting. Online grocery stores may use consumer self-generated technology-enabled healthy food labels to increase revenue by increasing preference for healthy food products.

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Table 1

Concept Profiles, the Independent Variables, and Their Corresponding Levels

Concept profile	Traffic Light Healthy Bar	Store's Healthy Bar	Your Healthy Bar	Delivery time	Price
1	30%	70%	70%	30 minutes	£60
2	30%	30%	Absent	30 minutes	£60
3	Absent	70%	70%	Next day	£60
4	70%	Absent	30%	Next day	£60
5	70%	70%	30%	In two days	£60
6	Absent	Absent	Absent	In two days	£60
7	Absent	Absent	30%	30 minutes	£70
8	70%	70%	Absent	30 minutes	£70
9	30%	30%	30%	Next day	£70
10	Absent	70%	Absent	Next day	£70
11	30%	Absent	70%	In two days	£70
12	70%	Absent	70%	30 minutes	£80
13	Absent	30%	30%	30 minutes	£80
14	30%	Absent	Absent	Next day	£80
15	70%	30%	70%	In two days	£80

16	30%	70%	30%	In two days	£80

Note. This table shows each concept number, their independent variables, and their corresponding levels. These were shown in random order.

Table 2

Results From the Multiple Regression Analysis

Predictor variables	Estimate	SE	t-value	p-value
Intercept	4.21440	0.02432	173.297	0.000000
Traffic Light Healthy Bar: 70%	0.56632	0.03492	16.219	0.000000
Traffic Light Healthy Bar: 30%	-0.43172	0.03274	-13.188	0.000000
Store's Healthy Bar: 70%	0.52704	0.03395	15.5188	0.000000
Store's Healthy Bar: 30%	-0.34777	0.03832	-9.075	0.000000
Your Healthy Bar: 70%	0.87228	0.03492	24.982	0.000000
Your Healthy Bar: 30%	-0.65885	0.03274	-20.127	0.000000
Delivery time: 30 minutes	0.13691	0.03274	4.182	0.000029
Delivery time: Next day	0.12276	0.03478	3.530	0.000421
Price: £60	0.05810	0.03290	1.766	0.077465
Price: £70	0.21458	0.03499	6.133	0.000000

Note. This table shows the results from the multiple regression analysis. Predictor variables are in the first column, estimates in the second, standard error (SE) in the third, t-value in the fourth, and p-value in the last column.

Table 3

Results From the Consumer Habit Questions

Questions	n	%
Behavior		
<u>How often do you order groceries online?</u>		
At least once a week.	45	22%
At least once a month.	55	27%
At least once every 2nd or 3rd month.	30	15%
At least once every 6th month.	15	7%
At least once every year.	33	16%
I have never ordered groceries online.	26	13%
<u>Do you find that ordering groceries online requires a lot of effort on your part?</u>		
Yes.	35	20%
To some extent.	80	45%
No.	63	33%
<u>Do you spend time figuring out whether a food product is healthy when grocery shopping?</u>		
Yes.	42	21%
To some extent.	114	56%
No.	48	24%

<u>Do you find it expensive to do online grocery shopping?</u>		
Yes.	52	29%
To some extent.	85	48%
No.	41	23%
<u>Do you look for healthy food labels when doing grocery shopping?</u>		
Yes.	48	27%
To some extent.	90	51%
No.	40	22%
<u>Have you seen other healthy food that are made possible by the use of technology in online grocery stores?</u>		
Yes.	39	22%
No.	139	78%
Consequences		
<u>Do you manage to find the product you want when ordering food from online stores?</u>		
Yes.	94	53%
To some extent.	80	45%
No.	4	2%

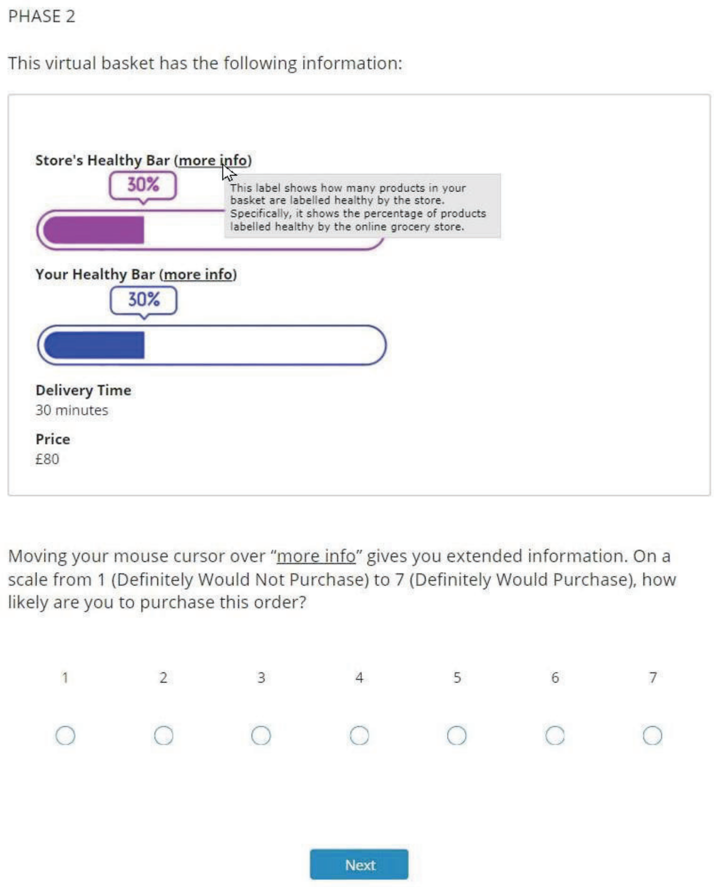
<u>Do you find online grocery stores reliable in providing the products you ordered?</u>		
Yes.	71	40%
To some extent.	87	49%
No.	20	11%
<u>Do you think the delivery time for online grocery shopping is too long?</u>		
Yes.	25	12%
To some extent.	58	28%
No.	121	59%
Antecedent Stimuli		
<u>Do you think there are too many online grocery stores to choose from?</u>		
Yes.	18	9%
To some extent.	40	20%
No.	146	72%
<u>Through what channel do you prefer to shop for groceries?</u>		
I prefer to use physical stores.	67	38%
I prefer to use online stores.	18	10%
I prefer to use both physical and online stores.	41	23%
I use both, but I mostly prefer physical stores.	36	20%
I use both, but I mostly prefer online stores.	16	9%

What would your initial reaction be if you saw one of the labels in this study in an online grocery store?		
It would be positive.	104	58%
It would be neutral.	70	39%
It would be negative.	4	2%
Do you find information about healthy food labels helpful or confusing?		
I find information related to healthy food labels helpful.	167	82%
I find information related to healthy food labels confusing.	37	18%
Do you find it easy to spot healthy food labels when you do your online grocery shopping?		
Yes.	49	28%
To some extent.	88	49%
No.	41	23%
Are you willing to purchase healthy food products at a higher price?		
Yes.	33	16%
To some extent.	124	61%
No.	47	23%

Note. This table shows the consumer habit questions, response options, number of participants that selected each response, and percentage of responses to each question.

Figure 1

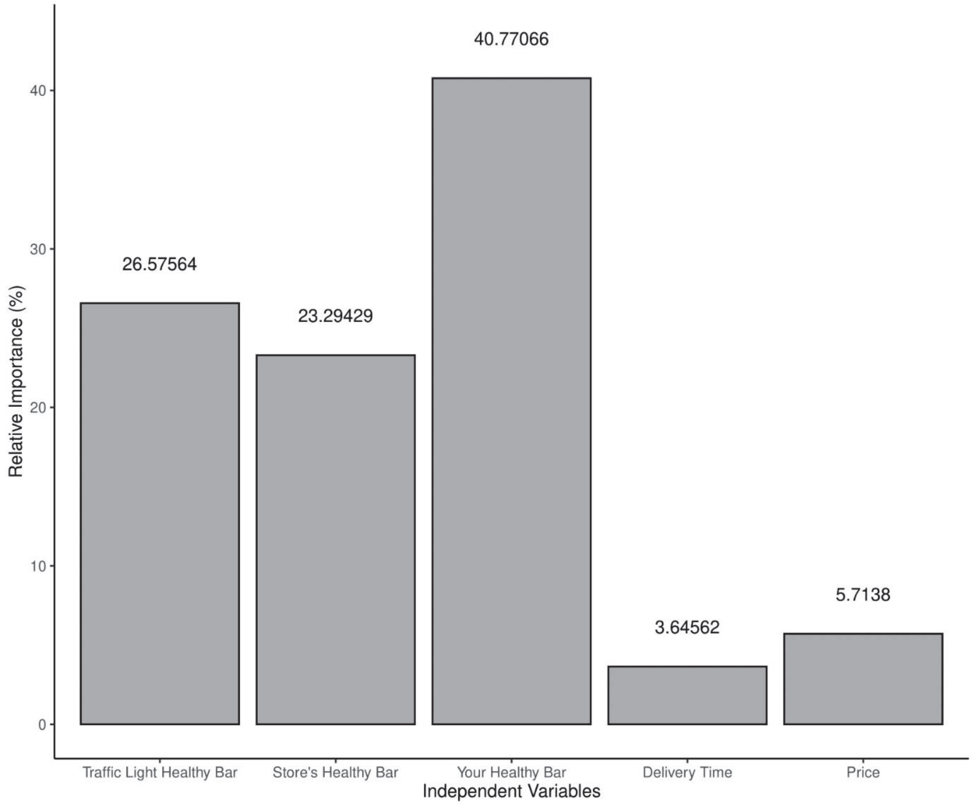
An Example Trial in the Conjoint Experiment



Note. This example trial shows profile 13. Labels were adapted from: Progress loading bar. Vector download graphic. 10 to 100 completed stock illustration (Elena_Garder, 2021). Retrieved from: https://www.istockphoto.com/vector/progress-loading-bar-vector-download-graphic-10-to-100-completed-gm1321814717-407954095?phrase=progress+loading+bar

Figure 2

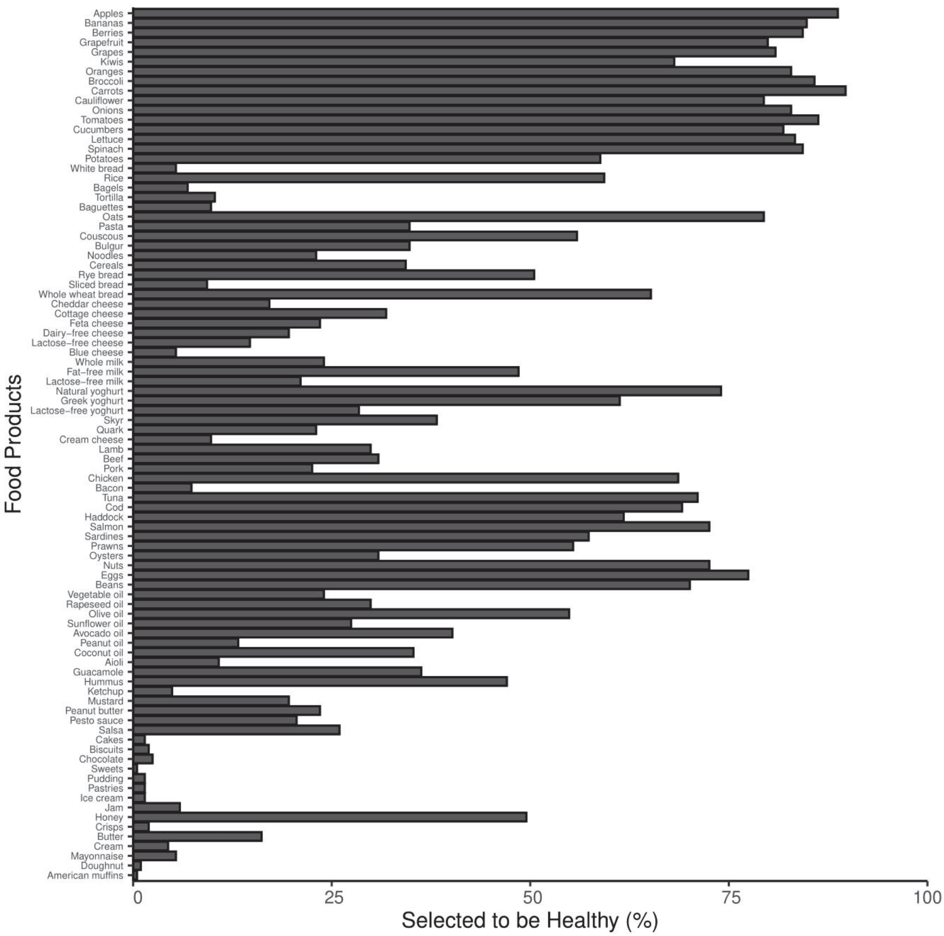
The Relative Importance Scores for the Independent Variables



Note. The relative importance is indicated on the vertical axis and each independent variable is shown at the vertical axis.

Figure 3

Healthy Products that Were Selected by the Participants



Note. The vertical axis shows the food item and the horizontal axis shows the percentage of participants that selected the corresponding food item as healthy. Percentage was calculated by dividing the number of participants who selected the food product by the total number of participants who completed the study.

Traffic-Light Healthy Bar

Option 1 (correct): This label shows how many products in your basket are labelled healthy by the Traffic Light Food Labelling System. Specifically, it shows the percentage of products with at least one green nutrient.

Option 2: This label shows how many products in your basket are labelled unhealthy by the Traffic Light Food Labelling System. Specifically, it shows the percentage of products with at least one red nutrient.

Option 3: This label shows the salt content in your basket. Specifically, it shows the percentage of the recommended salt content for a week.

Store's Healthy Bar

Option 1 (correct): This label shows how many products in your basket are labelled healthy by the store. Specifically, it shows the percentage of products labelled healthy by the online grocery store.

Option 2: This label shows how many products in your basket are labelled unhealthy by the store. Specifically, it shows the percentage of products labelled unhealthy by the store.

Option 3: This label shows how many healthy products in your basket are on discount. Specifically, it shows the percentage of healthy products that were on discount.

Your Healthy Bar

Option 1 (correct): This label shows how many products in your basket are labelled healthy by your standards. Specifically, it shows the percentage of products labelled healthy based on your perception of what healthy is.

Option 2: This label shows how many products in your basket are labelled healthy by other similar consumers. Specifically, it shows the percentage of products labelled healthy based on other consumers' evaluations.

Option 3: This label shows how many products in your basket are labelled unhealthy by your standards. Specifically, it shows the percentage of products labelled unhealthy based on your choices.

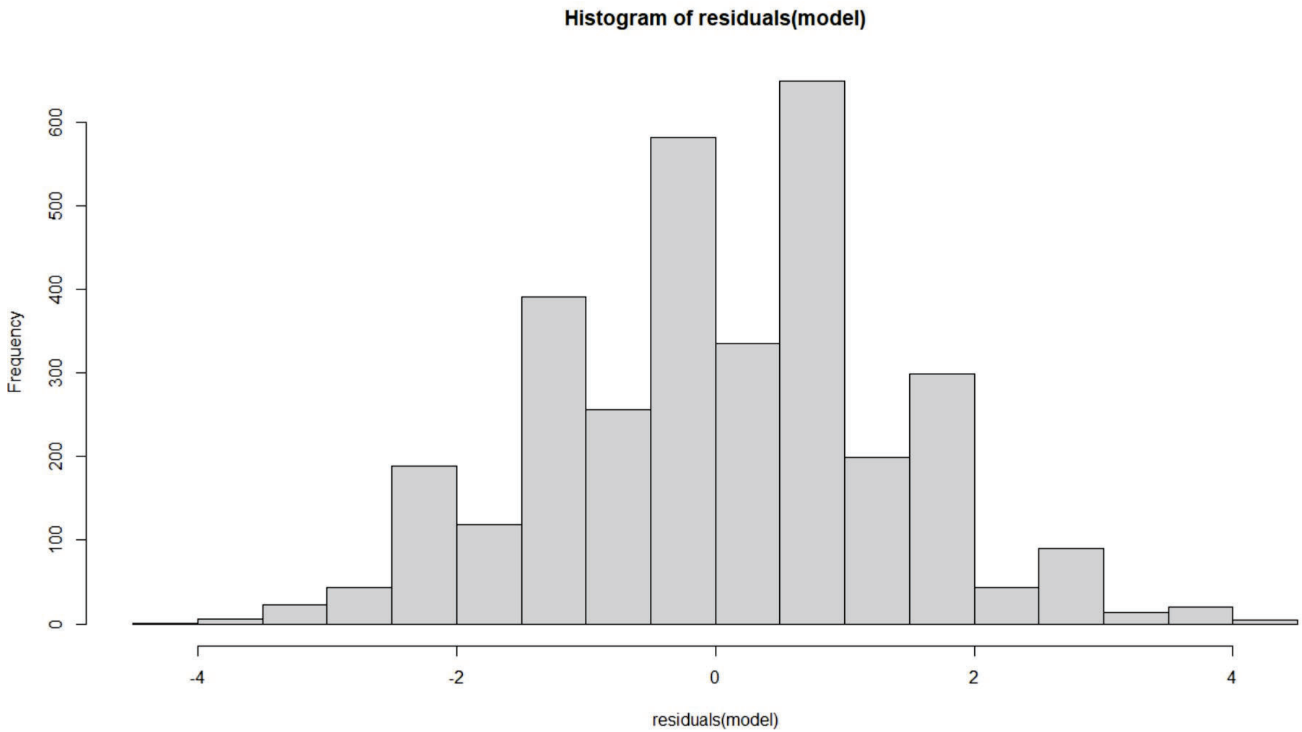
SA Table 1

Generalized Variance Inflation Factor Test

Independent variables	Generalized Variance Inflation Factor	Degrees of Freedom	Generalized Variance Inflation Factor ^(1/(2*Degrees of Freedom))
Traffic-Light Healthy Bar	1.145469	2	1.03514
Store’s Healthy Bar	1.184373	2	1.043211
Your Healthy Bar	1.135369	2	1.034514
Delivery Time	1.145369	2	1.034514
Price	1.214445	2	1.049771

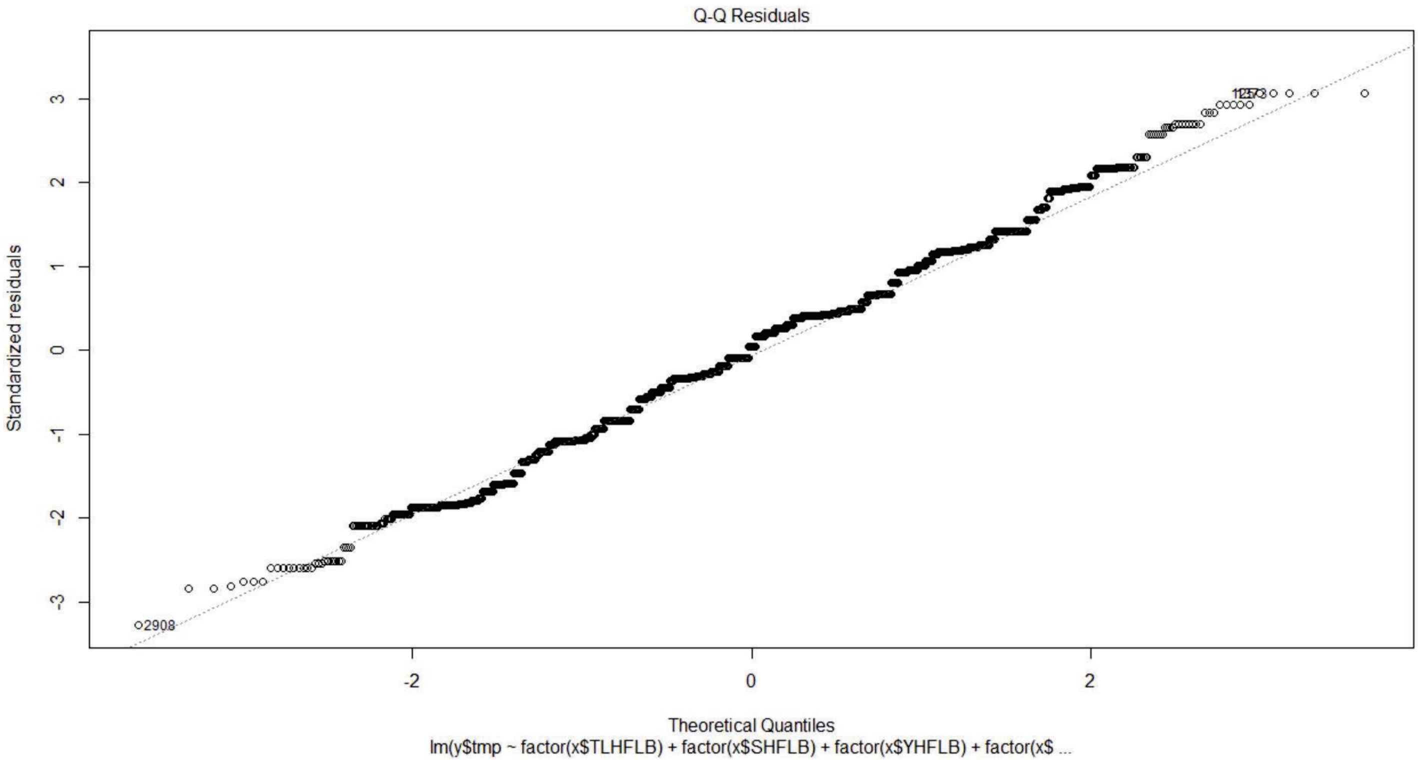
SA Figure 1

Frequency of the residuals of the model.



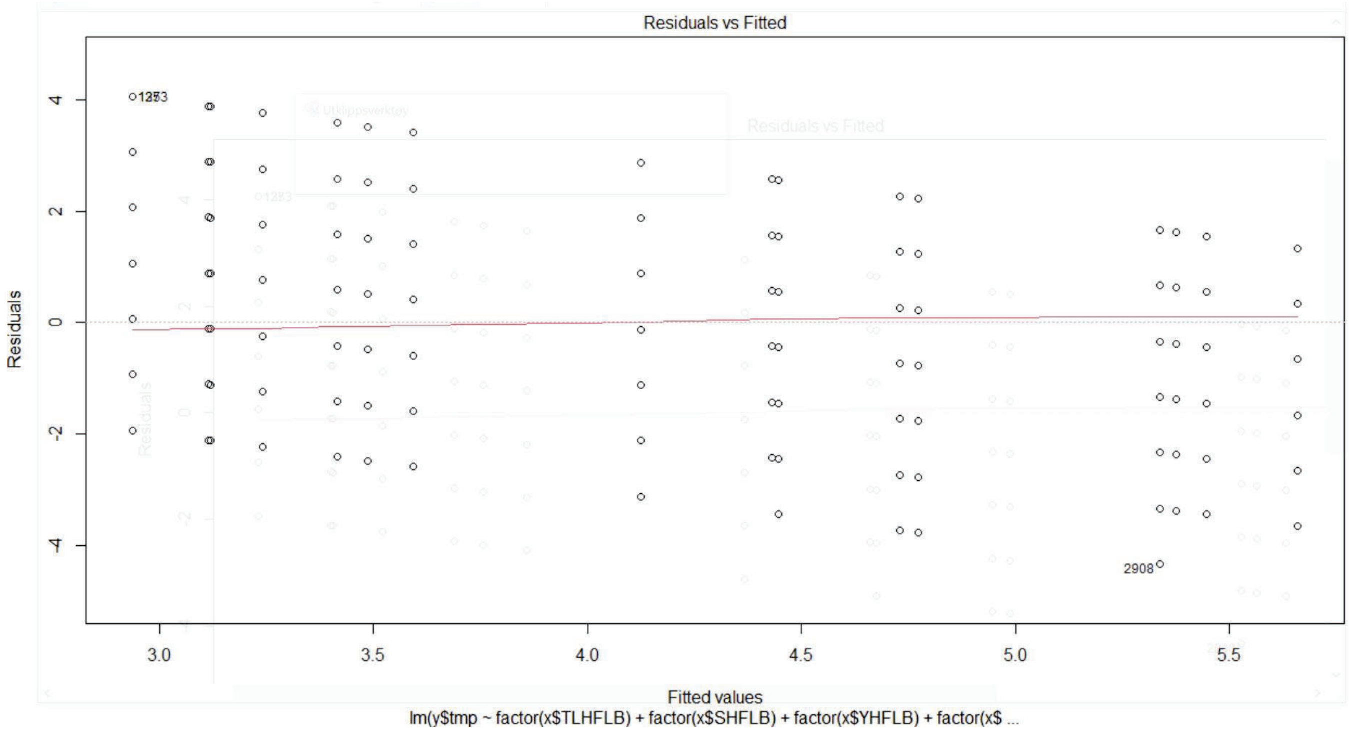
SA Figure 2

Q-Q Plot of Standardized Residuals and Theoretical Quantiles



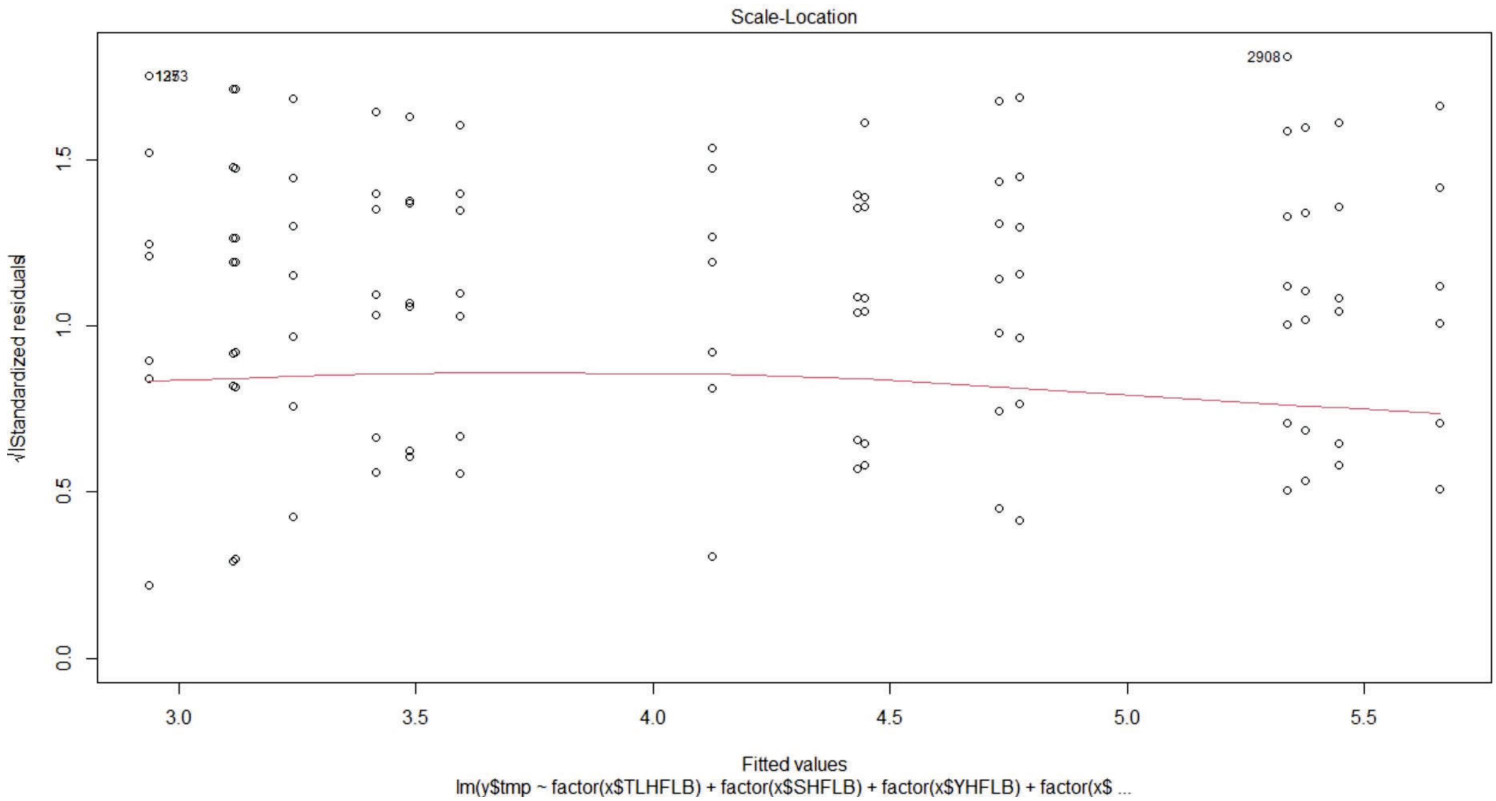
SA Figure 3

Residuals and Fitted Values



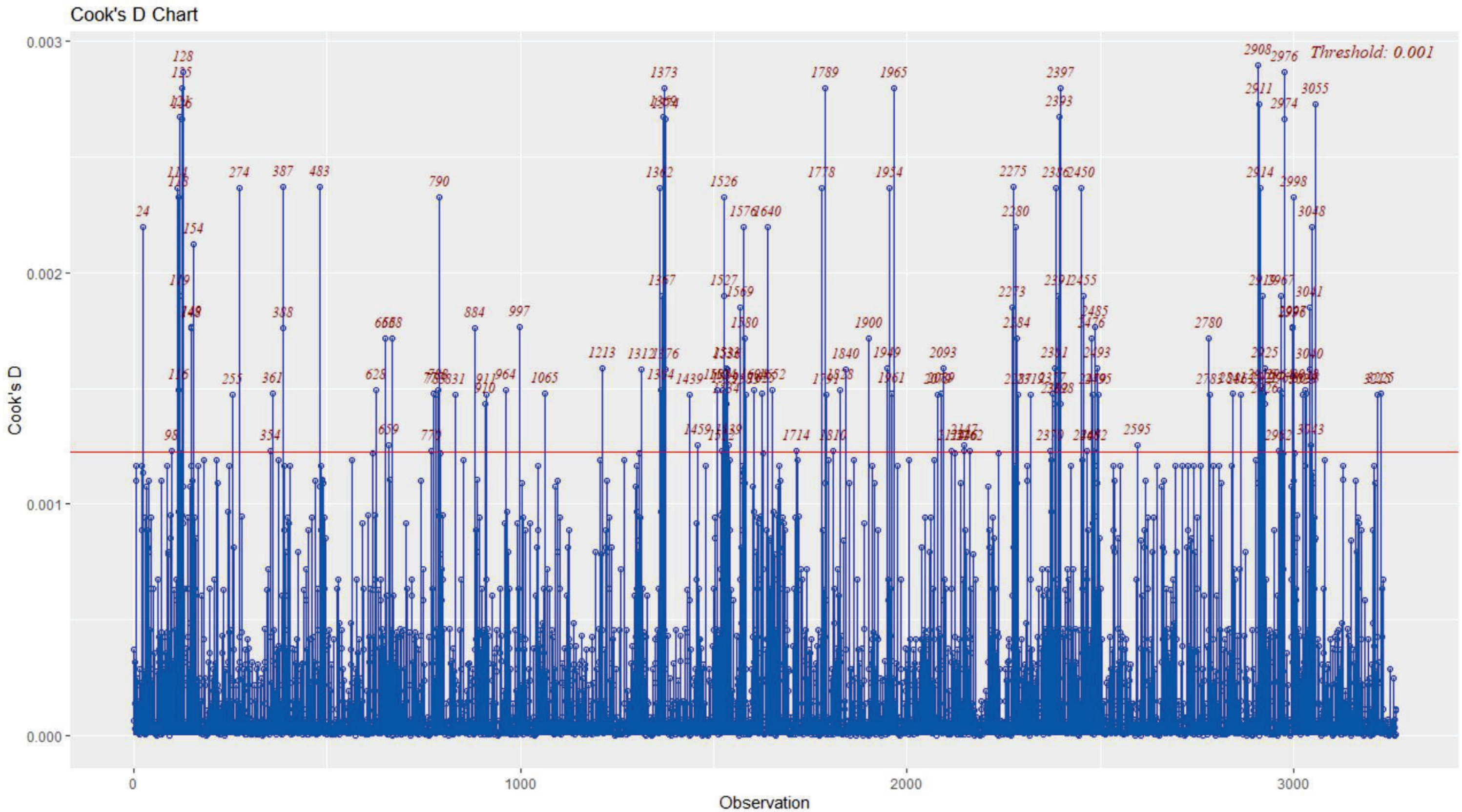
SA Figure 4.

Square Root of Standardized Residuals over Fitted Values



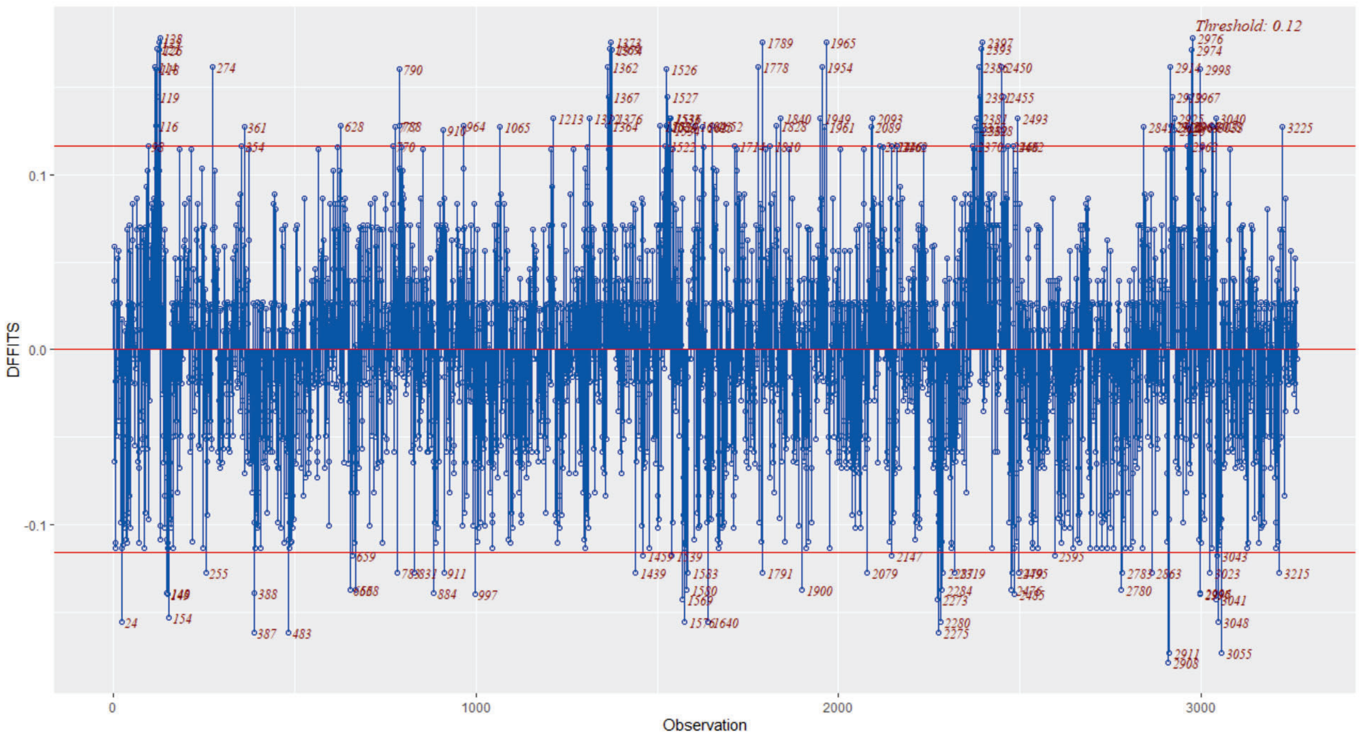
SA Figure 5

Cook's Distance



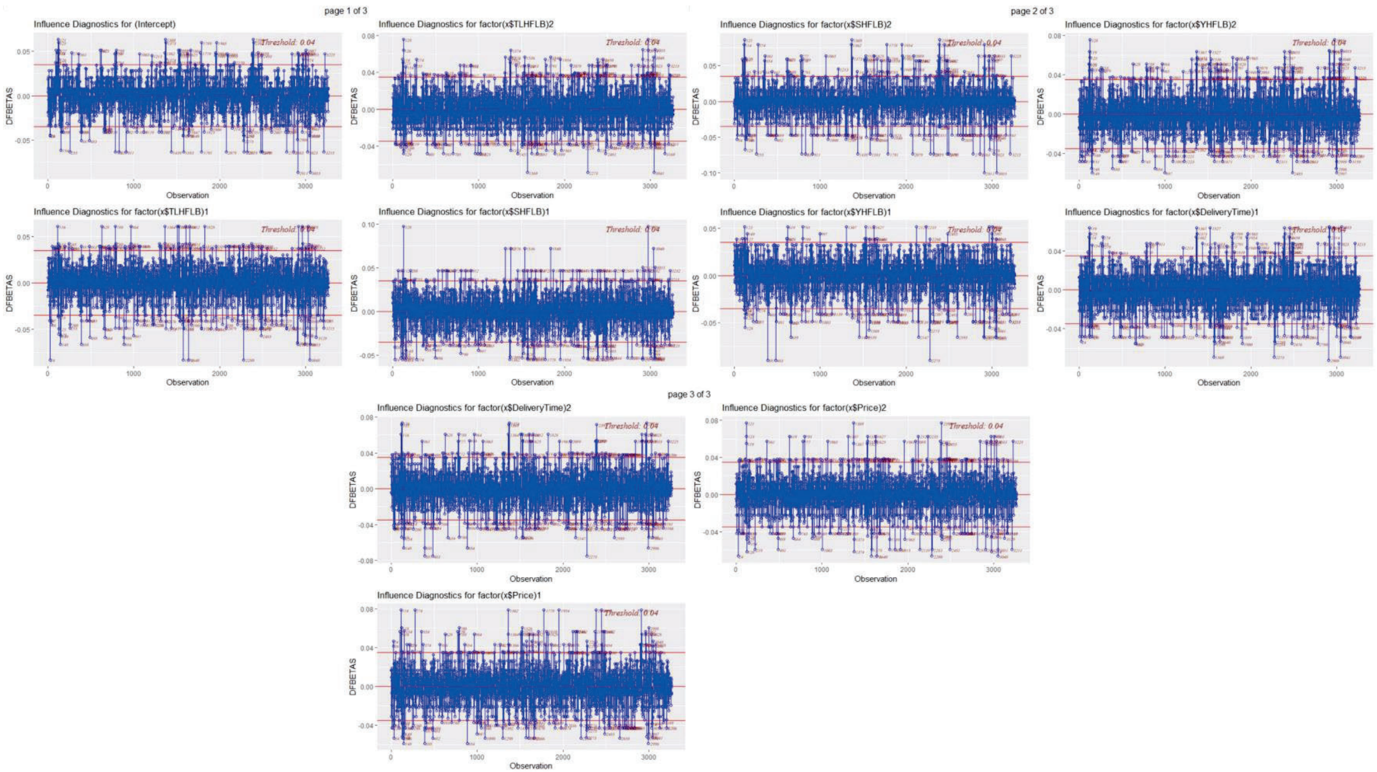
SA Figure 6

DFFITS Across Each Observation



SA Figure 7

DFBETAS Across Each Observation



```
library(conjoint)

library(ggplot2)

library(broom)

library(tidyverse)

library(MASS)

library(lmtest)

library(BrailleR)

library(olsrr)

library(moments)

library(car)

library(dplyr)

library(tidyr)

library(reshape2)

library(readr)

library(psych)



Dataset <- read_csv("Dataset.csv")

View(Dataset)
```

```
# Creating all possible combinations of the levels.
sources <- expand.grid(
  TLHFLB = c("TL70%", "TL30%", "TLabsent"),
  SHFLB = c("S70%", "S30%", "Sabsent"),
  YHFLB = c("Y70%", "Y30%", "Yabsent"),
  DeliveryTime = c("30 min", "Next day", "In two days"),
  Price = c("60GBP", "70GBP", "80GBP"))

# Creates a fractional factorial design based on IVs and levels.
sourcesfactdesign <- caFactorialDesign(data = sources, type = "fractional")
print(sourcesfactdesign)

# Recodes fractional factorial design to have 1 as the first level, 2 as the
second,
# and 3 as the third. It prints a correlation matrix of these.
```

```
prof=caEncodedDesign(design=sourcesfactdesign)

prof

print(cor(prof))

write.csv(prof, "C:/Users/nilj002/Desktop/Files/Research articles in
progress/What is healthy anyways Conjoint Experiment/copydesign.csv",
row.names=FALSE)


# Level names are written here.

levelnames = c("TL70%", "TL30%", "TLabsent",

        "S70%", "S30%", "Sabsent",

        "Y70%", "Y30%", "Yabsent",

        "30 min", "Next day", "In two days",

        "60GBP", "70GBP", "80GBP")

print(levelnames)


# Import the dataframe here (Data has been imported by using "Import
Dataset")
```

```
wholedata <- Dataset

wholedata <- as.data.frame(Dataset)

# Create dataframe for conjoint experiment

conjointexperimentdata <- wholedata[, colnames(wholedata)[c(113:128)]]

# Create dataframe for Healthy Food selected

healthyfoodselecteddata <- wholedata[, colnames(wholedata)[c(23:112)]]

# Create dataframe for consumer habit

consumerhabitdata <- wholedata[, colnames(wholedata)[c(129:143)]]




# Call the original Conjoint function with effects coding

Conjoint(conjointexperimentdata, prof, levelnames)



# Additional functions were used from this source:
https://rdrr.io/cran/conjoint/src/R/ENGINE.R#sym-utilities

# NEwcaUtilities is used to use other functions of the model in order to
check for model
```

```
# assumptions. Conjoint() alone cannot do this. Dummy variable coding is used here instead
# of effects coding.


NewcaUtilities <- function (y, x, z)
{
  options(contrasts = c("contr.sum", "contr.poly"))
  outdec <- options(OutDec = ".")
  on.exit(options(outdec))
  options(OutDec = ",")
  y <- m2v(y)
  m <- length(x)
  n <- nrow(x)
  S <- nrow(y)/n
  xnms <- names(x)
  ynms <- names(y)
  xtmp <- paste("factor(x$", xnms, sep = "", paste(")")) ##########
  xfrm <- paste(xtmp, collapse = "+")
  yfrm <- paste("y$", ynms, sep = "", "~")
```

```
  frml <- as.formula(paste(yfrm, xfrm))
  Lj <- vector("numeric", m)
  for (j in 1:m) {
    Lj[j] <- nlevels(factor(x[[xnms[j]]]))
  }
  x <- as.data.frame(matexpand(m, n, S, x))
  camodel <- lm(y$tmp ~ factor(x$TLHFLB) + factor(x$SHFLB) +
factor(x$YHFLB) +
              factor(x$DeliveryTime) + factor(x$Price))
  #New code is added here
  print(summary.lm(camodel)) # Summary of code is added here
  u <- as.matrix(camodel$coeff)
  intercept <- u[1]
  ul <- utilities(u, Lj)
  utlsplot(ul, Lj, z, m, xnms)
  uli <- c(intercept, ul)
  return(camodel)
}
```

```
m2v <- function (y, w = TRUE)
{
 y <- as.matrix(y)
 if (w) {
  S <- nrow(y)
  n <- ncol(y)
 }
 else {
  S <- ncol(y)
  n <- nrow(y)
 }
 tmp <- vector("numeric", S * n)
 k <- 0
 for (i in 1:S) {
  for (j in 1:n) {
   k = k + 1
   if (w)
    tmp[k] <- y[i, j]
   else tmp[k] <- y[j, i]
  }
```

```
 }
 ytmp <- as.data.frame(tmp)
 return(ytmp)
}


matexpand <- function(m, n, S, x)
{
 N <- n*S
 X <- matrix(0, N, m)
 k <- 1
 for(s in 1:S)
 {
  for(i in 1:n)
  {
   for(j in 1:m) {X[k,j] <- x[i,j]}
   k <- k+1
  }
 }
 colnames(X) <- names(x)
```

```
  return(X)
}


utilities <- function(u, Lj)
{
  m <- length(Lj)
  L <- sum(Lj)
  p <- length(u)
  b <- vector("numeric", p-1)
  ul <- vector("numeric", L)
  for(i in 1:(p-1)) {b[i] <- u[i+1]}
  i <- 0
  h <- 1
  for(j in 1:m)
  {
    tu <- 0
    l <- Lj[j]-1
    for (k in 1:l)
    {
      i <- i+1
```

```
      ul[i] <- b[h]
      tu <- tu+ul[i]
      h <- h+1
    }
    i <- i+1
    ul[i] <- -tu
  }
  return(ul)
}

utlsplot<-function(ul,Lj,z,m,xnms)
{
  zz<-as.matrix(z)
  i<-1
  for(j in 1:m)
  {
    l<-Lj[j]
    lb<-vector("numeric",l)
    ln<-vector("character",l)
    for (k in 1:l)
```

```
  {
   lb[k]<-ul[i]
   ln[k]<-zz[i]
   i<-i+1
  }
  a<-abs(min(lb))+abs(min(lb))
  b<-abs(max(lb))+abs(max(lb))
  dev.new(width=5,height=5,pointsize=9)
  barplot(lb,ylim=c(-a,b),ylab="utility",xlab=xnms[j],names.arg=ln)
 }
 return(0)
}
```

```
# Runs the regression analysis (ignore the plots of the effects coding estimates, see the console for dummy variable coding)
model <- NewcaUtilities(y=conjointexperimentdata, x=prof, z=levelnames )
summary(model)
```

```
ols_plot_added_variable(model)

# General diagnostics test for regression analysis. Visual test of linearity,

# homosckedasticity, normality of predicted errors, and outliers.

plot(model)

# Normal distribution test

hist(residuals(model))

shapiro.test(rstandard(model))

skewness(residuals(model))

# Linearity test

plot(y = resid(model), fitted(model))

resettest(model)

# Homoskcedasticity test

ncvTest(model)

plot(fitted(model), sqrt(abs(rstandard(model))))

# Multi-collinearity

vif(model)

# Outliers, influential and leverage points

plot(cooks.distance(model))

plot(dffits(model))

ols_plot_dffits(model)
```

```
ols_plot_cooksd_chart(model)

ols_plot_dfbetas(model)



#Additional test

WhereXY(y=residuals(model), fitted.values(model)) #test for overlapping
datapoints

print(round(cov(prof),5))

print(round(cor(prof), 5))



#Calculating relative importance by finding the range of

#estimates within one independent variable.



rangevaluesTLHB <- c(0.56632, -0.43172)

rangevaluesSHB <- c(0.52704, - 0.34777)

rangevaluesYHB <- c(0.87228, - 0.65885)

rangevaluesDeliveryTime <- c(0.13691, - 0)
```

```
rangevaluesPrice <- c(0.21458, - 0)

sum(rangevaluesTLHB, rangevaluesSHB,rangevaluesYHB,
rangevaluesDeliveryTime, rangevaluesPrice)

rangeTLHB <- diff(range(rangevaluesTLHB))

rangeSHB <- diff(range(rangevaluesSHB))

rangeYHB <- diff(range(rangevaluesYHB))

rangeDeliveryTime <- diff(range(rangevaluesDeliveryTime))

rangePrice <- diff(range(rangevaluesPrice))

rangeTLHB

rangevaluesSHB

rangevaluesYHB

rangevaluesDeliveryTime

rangevaluesPrice



sum(rangeTLHB, rangeSHB, rangeYHB, rangeDeliveryTime, rangePrice)


#Relative Importance value of the estimates

#Traffic Light Healthy Bar
```

```
RelImpValTLHB <- (rangeTLHB / (rangeTLHB + rangeSHB + rangeYHB +
rangeDeliveryTime + rangePrice))

#Store's Healthy Bar

RelImpValSHB <- (rangeSHB / (rangeTLHB + rangeSHB + rangeYHB +
rangeDeliveryTime + rangePrice))

#Your Healthy Bar

RelImpValYHB <- (rangeYHB / (rangeTLHB + rangeSHB + rangeYHB +
rangeDeliveryTime + rangePrice))

#Delivery Time

RelImpValDeliveryTime <- (rangeDeliveryTime / (rangeTLHB + rangeSHB +
rangeYHB + rangeDeliveryTime + rangePrice))

#Price

RelImpValPrice <- (rangePrice / (rangeTLHB + rangeSHB + rangeYHB +
rangeDeliveryTime + rangePrice))


#Checking if these adds up to 100%

sum(RelImpValTLHB, RelImpValSHB, RelImpValYHB,
RelImpValDeliveryTime, RelImpValPrice)
```

```
NamesOfIVs <- c("Traffic Light Healthy Bar","Store's Healthy Bar", "Your
Healthy Bar", "Delivery Time", "Price")

RelImpVal <- c(RelImpValTLHB, RelImpValSHB, RelImpValYHB,
RelImpValDeliveryTime, RelImpValPrice)




relativeimpact <- data.frame(RelImpVal, NamesOfIVs)

relativeimpact$NamesOfIVs = factor(relativeimpact$NamesOfIVs, levels =
c("Traffic Light Healthy Bar","Store's Healthy Bar", "Your Healthy Bar",
"Delivery Time", "Price"))



# Visual representation of relative importance score

ggplot(relativeimpact, aes(x=NamesOfIVs, y=RelImpVal)) +
  geom_bar(stat = "identity", color = "black", fill = "darkgray") +
  scale_y_continuous(labels = function(x) format(x*100,digits=2)) +
  labs(y = "Relative Importance (%)", x = "Independent Variables") +
  geom_text(aes(label = round(RelImpVal*100, 5)), nudge_y = 0.025) +
  theme_classic()
```

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