Obesity and Food Choice: A Survey of Cognitive and Temporal Influences on Decision-Making

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Abstract

This survey explores the interconnected concepts of obesity and food choice, focusing on how episodic future thinking (EFT) and delay discounting influence cognitive behavior and decision-making processes. The paper is structured to examine the multifaceted nature of obesity, encompassing genetic, social, and environmental determinants that shape dietary behaviors. It delves into the role of EFT in reducing impulsive decisions by enhancing the perceived value of delayed rewards, thereby promoting healthier food choices. The survey also evaluates the impact of temporal discounting on cognitive behavior and decision-making, supported by theoretical frameworks and psychological mechanisms. Methodological advances in measuring decision-making processes are highlighted, emphasizing the importance of rapid assessment techniques and training paradigms. The paper reviews interventions aimed at modifying EFT and delay discounting, including technology-driven approaches that leverage machine learning and predictive analytics to personalize dietary recommendations. The survey concludes by underscoring the need for comprehensive strategies that integrate genetic, environmental, and cognitive factors to address the global obesity epidemic. Future research directions include expanding datasets to diverse populations, refining intervention models, and exploring the neurobiological underpinnings of decision-making processes related to food choices. By synthesizing these diverse influences, the survey aims to inform effective public health strategies that promote healthier lifestyles and mitigate the impact of obesity.

1 Introduction

1.1 Structure of the Survey

This survey is structured into several key sections that address distinct yet interrelated components of obesity and food choice. The *Introduction* outlines the survey's scope and significance, highlighting the connections among obesity, food choice, episodic future thinking, delay discounting, cognitive behavior, temporal discounting, and decision-making. The subsequent *Background and Definitions* section provides a detailed overview of core concepts, defining each term and clarifying their interrelations.

The section on *Obesity and Food Choice* explores the dynamics between obesity and food selection, considering both individual and societal influences. Following this, the *Episodic Future Thinking and Delay Discounting* section examines how episodic future thinking affects delay discounting and decision-making processes. The impact of temporal discounting on cognitive behavior is analyzed in the *Cognitive Behavior and Temporal Discounting* section, supported by relevant theoretical frameworks and psychological mechanisms.

The *Decision-Making Processes* section delves into the methodologies used to measure decision-making in food choice. This is followed by a review of *Interventions and Implications*, which assesses strategies aimed at modifying episodic future thinking and delay discounting to encourage healthier

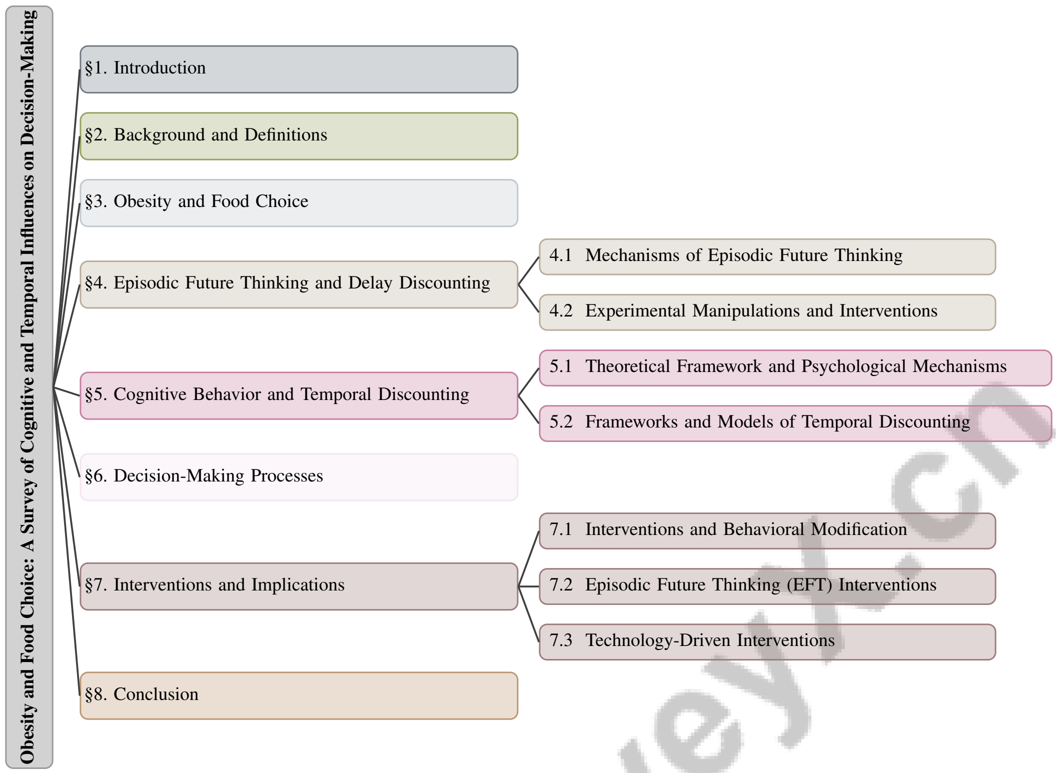

Figure 1: chapter structure

food choices. The survey concludes with a *Conclusion* that synthesizes key findings and discusses future research trajectories, reinforcing the interconnectedness of the examined concepts.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Definitions and Health Implications of Obesity

Obesity, a chronic condition characterized by excessive body fat, poses significant health risks, including type 2 diabetes, cardiovascular diseases, and certain cancers [1]. Its prevalence, particularly among adolescents, is alarming and linked to severe health outcomes such as prediabetes [1]. This condition results from a complex interplay of genetic, hormonal, and environmental factors, positioning it as a critical public health challenge [1]. The rise of online-to-offline (O2O) food delivery platforms exacerbates this issue by promoting unhealthy dietary choices, underscoring the impact of socio-economic and technological factors on eating habits [2]. Delay discounting, a cognitive bias where immediate rewards are favored over delayed ones, further perpetuates poor dietary decisions and obesity [3]. Addressing the multifaceted nature of obesity is essential for developing effective public health strategies.

2.2 Determinants of Food Choice

Determinants of food choice are influenced by cognitive, social, and environmental factors. Cognitive determinants, notably affected by temporal discounting, complicate the promotion of healthier diets as the perceived value of delayed rewards diminishes [4]. Economic scarcity intensifies this bias, leading to a preference for immediate gratification over long-term health benefits [5]. Genetic influences, such as insulin resistance and the gut microbiome, also play a critical role in dietary preferences [6].

Social factors significantly impact dietary decisions, especially in communal settings. Research on food purchases linked via smartcards illustrates the influence of social ties and shared meals on dietary habits [7]. Social mimicry in food consumption highlights peer influence in shaping food choices

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[8]. The stigma surrounding obesity and limited access to treatment options further complicate social dynamics [9].

Environmental determinants, including economic factors and food delivery systems, notably influence dietary behaviors. The emergence of O2O food delivery platforms has shifted consumption patterns towards convenience over nutrition [2]. Additionally, the abundance of information and scarcity of appealing healthy options hinder healthier eating habits [10]. Understanding these interconnected determinants is crucial for developing interventions that effectively modify food choices, addressing the ineffectiveness of current weight loss strategies [1].

In examining the multifaceted nature of obesity, it is crucial to consider the various factors that contribute to food choices and dietary behaviors. As illustrated in Figure 2, the hierarchical structure of these factors reveals a complex interplay between genetic predispositions, environmental influences, and social determinants. This figure categorizes the interrelation of obesity and food choice, emphasizing key elements such as genetic and environmental influences, as well as potential interventions that can mitigate these effects. By understanding this intricate framework, we can better address the challenges posed by obesity in contemporary society.

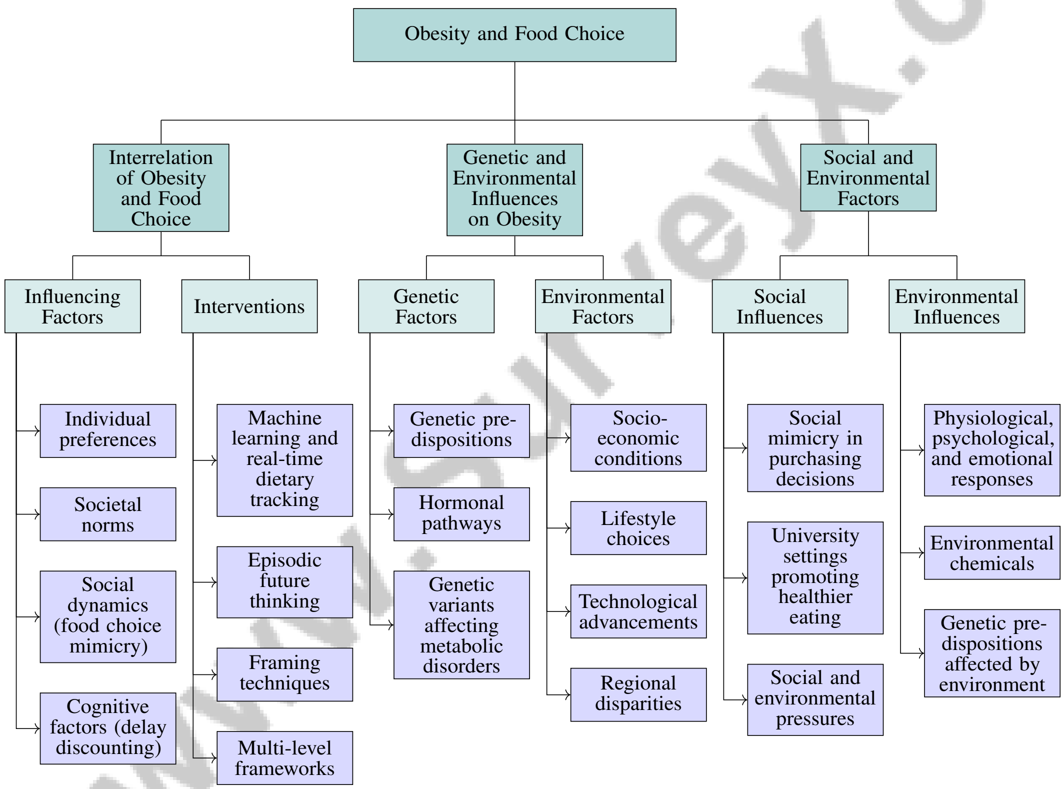

Figure 2: This figure illustrates the hierarchical structure of factors influencing obesity and food choices. It categorizes the interrelation of obesity and food choice, genetic and environmental influences, and social and environmental factors, highlighting key influencing elements and interventions.

3 Obesity and Food Choice

3.1 Interrelation of Obesity and Food Choice

The intricate relationship between obesity and food choice is influenced by individual preferences and societal norms. Machine learning and real-time dietary tracking offer insights into how predictive analytics can shape food choices, facilitating personalized interventions for healthier eating [11]. Social dynamics, such as food choice mimicry, where individuals emulate peers' eating habits, significantly affect dietary patterns and contribute to obesity [8]. Cognitive factors, notably delay discounting, further complicate food choice, as higher rates lead to poorer health behaviors, exacerbating obesity

[12]. Interventions like episodic future thinking and framing have shown potential in improving dietary decisions and reducing obesity risk [13]. The absence of a unified framework for intervention components complicates understanding societal influences on obesity [14]. Multi-level frameworks integrating experimental, translational, and formal models are necessary to comprehend food choice determinants [15], informing effective interventions to alter food preferences and mitigate societal dietary pressures.

3.2 Genetic and Environmental Influences on Obesity

Obesity is shaped by the interplay between genetic predispositions and environmental factors. Genetic variants significantly contribute to obesity and related metabolic disorders, affecting food choices through hormonal pathways [16, 6]. Environmental factors, including socio-economic conditions, lifestyle choices, and technological advancements, are pivotal in shaping dietary behaviors. The integration of predictive modeling with dietary tracking highlights significant challenges in addressing obesity, offering comprehensive systems to influence dietary behaviors [11]. This integration is crucial for developing personalized interventions considering both genetic and environmental determinants to enhance obesity management. Recognizing the complex interplay of these factors enables targeted interventions promoting healthier lifestyles and mitigating obesity-related health risks, such as type 2 diabetes, cardiovascular diseases, and cancers. Understanding regional disparities and socio-economic factors can inform effective public health strategies to reduce the global obesity burden [6, 17, 16, 14, 18].

3.3 Social and Environmental Factors

Social and environmental factors are crucial in determining food choices, exerting pressures that shape dietary behaviors. As illustrated in Figure 3, these factors encompass key elements such as social mimicry, environmental impacts, and intervention strategies aimed at promoting healthier eating behaviors. Social mimicry in purchasing decisions, especially in university settings, indicates that social environments can promote healthier eating habits [8]. Environmental factors, including physiological, psychological, and emotional responses, complicate the relationship between social dynamics and food choice [15]. These influences often prioritize convenience over nutrition. Additionally, environmental chemicals significantly impact obesity and food preferences, highlighting the need for regulatory measures [6]. Genetic predispositions, such as BMI and waist-to-hip ratio, are influenced by environmental conditions, emphasizing the complex interaction between genetic traits and external factors [16]. Understanding these pressures enables the development of targeted interventions, such as policy changes to limit unhealthy food options and educational programs to raise awareness of social and environmental influences on dietary decisions. Such measures aim to address undernutrition and diet-related diseases [19, 20, 7], fostering healthier food choices and reducing obesity prevalence.

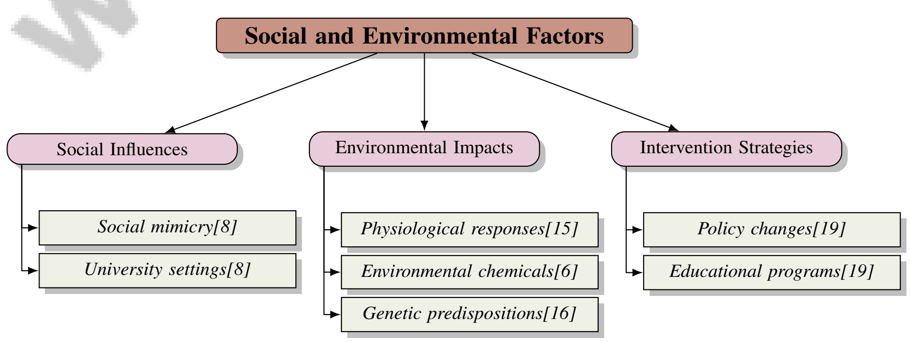

Figure 3: This figure illustrates the key social and environmental factors influencing dietary choices, highlighting social mimicry, environmental impacts, and intervention strategies to promote healthier eating behaviors.

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4 Episodic Future Thinking and Delay Discounting

4.1 Mechanisms of Episodic Future Thinking

Episodic future thinking (EFT) allows individuals to mentally simulate future scenarios, enhancing decision-making by valuing delayed rewards over immediate gratification [3]. Rooted in behavioral economics, particularly the hyperbolic discounting model, EFT promotes long-term benefits and reduces impulsivity, especially in adolescents as shown in delay discounting paradigms [21]. Engaging in EFT has been experimentally shown to decrease delay discounting, fostering healthier behavioral decisions [22]. This strategy is pivotal for dietary changes, aligning with broader goals of improving decisions regarding delayed rewards [23]. The reduction in impulsivity through EFT is essential for enhancing self-control in food choices, leveraging insights from extensive, passively sensed data to analyze social influences on dietary behavior [7].

Psychological mechanisms of EFT are further clarified through frameworks that categorize research based on theoretically relevant cues, aiding in understanding impulsivity variability, which can be quantitatively modeled [24, 25]. Integrating machine learning with health guidelines in food recommendation systems (FRS) underscores EFT's potential to guide users towards healthier food choices [10]. The interaction between stress hormones and impulsivity in temporal discounting reveals a complex relationship between physiological and cognitive factors in decision-making [26]. Understanding these mechanisms enables the design of targeted interventions using EFT to curb impulsive behaviors and promote healthier lifestyle choices, with its goal-oriented nature enhancing its effectiveness in reducing delay discounting [23].

4.2 Experimental Manipulations and Interventions

Experimental manipulations targeting EFT have effectively reduced delay discounting (DD) and improved decision-making. Stein et al. demonstrated EFT's significant impact on lowering DD, even under simulated economic scarcity, highlighting its practical applicability [5]. Rung et al. emphasized the environmental modulation of EFT's effectiveness when context-specific cues are present [24]. Methodologies such as the 5-trial adjusting-delay task facilitate EFT integration into natural settings, enabling rapid assessment of its effects on DD [27]. Ding et al. explored social media engagement's influence on DD behavior, using machine learning to analyze these interactions, suggesting social contexts' impact on EFT interventions [3].

EFT interventions have been rigorously evaluated through diverse experimental designs. Studies with Amazon Mechanical Turk participants interested in weight loss employed delay discounting tasks and food demand measures to compare EFT outcomes against controls [28]. These studies indicate that EFT enhances the ability to delay gratification, thus promoting healthier decision-making. The precision and reliability of EFT interventions are validated through statistical metrics, ensuring robust findings across different settings [29]. Khan et al. explored persuasive visualizations and nudging strategies, complementing EFT by providing health information related to food choices, reinforcing cognitive shifts induced by EFT [10].

To illustrate the comprehensive nature of these interventions, Figure 4 depicts the hierarchical structure of EFT interventions, detailing methodologies, effectiveness, and future directions. The methodologies include innovative tasks and online interventions, while the effectiveness highlights EFT's impact on delay discounting and its context-dependent nature. Future directions suggest optimizing interventions and exploring new contexts and models.

Despite promising results, analyses reveal that while many manipulation studies successfully reduce DD, fewer training-based studies achieve similar outcomes, suggesting short-term, focused interventions may be more effective [30]. This insight highlights the need for further research to refine EFT interventions, optimizing their impact on health behaviors and decision-making processes. Future research should explore the efficacy of EFT interventions in reducing DD and improving health outcomes, considering different models and frameworks to better understand DD behaviors [31]. By integrating goal-oriented and general episodic thinking under controlled conditions, EFT has the potential to significantly modulate decision-making processes, offering a promising strategy for enhancing self-control and promoting healthier lifestyle choices [23]. Through these experimental manipulations and interventions, EFT emerges as a vital tool in improving public health outcomes by fostering better decision-making and reducing obesity-related behaviors.

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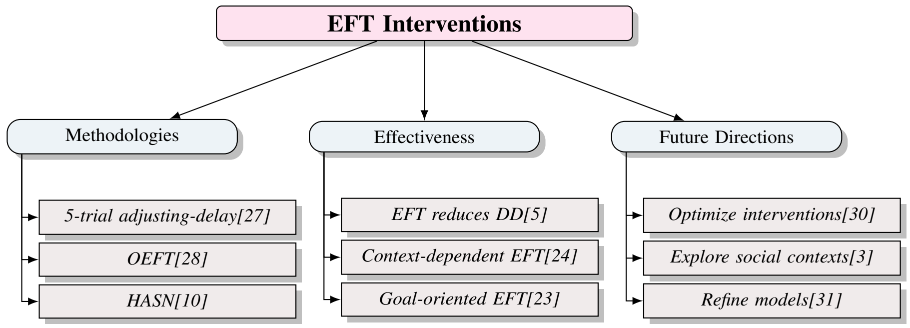

Figure 4: This figure illustrates the hierarchical structure of EFT interventions, detailing methodologies, effectiveness, and future directions. The methodologies include innovative tasks and online interventions. Effectiveness highlights EFT's impact on delay discounting and its context-dependent nature. Future directions suggest optimizing interventions and exploring new contexts and models.

5 Cognitive Behavior and Temporal Discounting

Cognitive behavior is intricately linked to temporal discounting, a process that influences how individuals prioritize immediate versus delayed rewards. This phenomenon is central to decision-making, as it encompasses various psychological mechanisms and theoretical frameworks that elucidate the variability in discounting behavior. The following subsection delves into these frameworks and mechanisms, offering a comprehensive understanding of temporal discounting and its implications for decision-making processes.

5.1 Theoretical Framework and Psychological Mechanisms

Temporal discounting is a cornerstone of decision-making, particularly in intertemporal choices where individuals evaluate smaller immediate rewards against larger delayed ones. Theoretical frameworks, such as hierarchical Bayesian modeling, enhance parameter estimation by leveraging information across individuals, providing a robust foundation for analyzing temporal discounting behaviors and controlling for confounding variables in social contexts [32, 7]. Psychological factors, including anxiety, significantly influence discounting, especially in individuals with psychiatric disorders [4]. These complexities necessitate comprehensive frameworks that integrate psychological states with temporal preferences, as illustrated by the super-statistics approach which accounts for social fluctuations affecting impulsivity [31].

Delay discounting is a modifiable risk factor pivotal for enhancing health behaviors and glycemic control, underscoring its relevance in public health interventions [12]. Individual differences in discounting are shaped by socio-economic, personality, cognitive, neural, and genetic factors, highlighting the variability across populations [33]. Nonmonetary outcomes are often discounted more steeply than monetary ones, reflecting the diverse nature of rewards and their impact on decision-making [34]. Quantitative models, like the two-stage analytical approach, simplify the quantification of discounting rates and their relation to participant characteristics [25]. Although these models advance our understanding of temporal discounting, they often struggle to generalize beyond specific testing conditions, posing challenges for broader applicability [24].

Figure 5 illustrates the hierarchical structure of theoretical frameworks and psychological mechanisms in temporal and delay discounting. This figure highlights key concepts such as hierarchical Bayesian modeling, psychological factors, and the super-statistics approach in temporal discounting. For delay discounting, it emphasizes modifiable risk factors, individual differences, and nonmonetary outcomes. Additionally, it incorporates quantitative models like the two-stage approach, along with strategies such as episodic future thinking and behavioral training, which are crucial for understanding and improving decision-making processes.

Integrating these frameworks and mechanisms enhances our understanding of temporal discounting, informing interventions to promote healthier decision-making. By examining factors influencing temporal preferences, researchers can develop strategies to bolster self-control and mitigate impulsive

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behaviors, leading to significant health improvements, as evidenced by studies on episodic future thinking and behavioral training techniques aimed at reducing delay discounting [13, 35, 21, 30, 20].

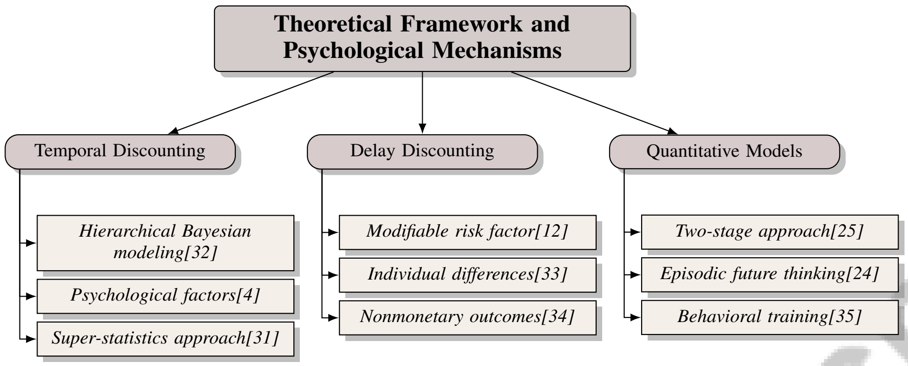


Figure 5: This figure illustrates the hierarchical structure of theoretical frameworks and psychological mechanisms in temporal and delay discounting. It highlights key concepts such as hierarchical Bayesian modeling, psychological factors, and the super-statistics approach in temporal discounting. For delay discounting, it emphasizes modifiable risk factors, individual differences, and nonmonetary outcomes. Quantitative models like the two-stage approach, episodic future thinking, and behavioral training are also included.

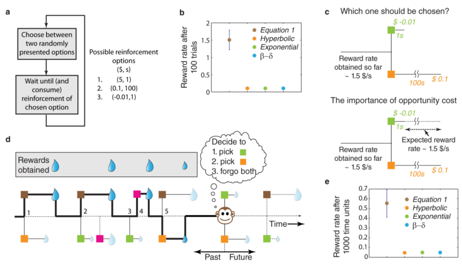
5.2 Frameworks and Models of Temporal Discounting

Temporal discounting involves evaluating the present value of future rewards, with various models elucidating the underlying mechanisms. The effective exponential model, incorporating fluctuations in impulsivity, offers a novel perspective on the Tsallis model of delay discounting, highlighting discounting behavior variability and the need for frameworks addressing individual differences [31]. The Bayesian Adaptive Design Optimization (ADO) method represents a significant advancement, using a computational algorithm to conduct adaptive experiments that select the most informative trials based on participant responses, achieving measurement objectives with minimal observations [29]. This optimization enhances the precision of temporal discounting measurements and facilitates exploring individual differences in discounting rates.

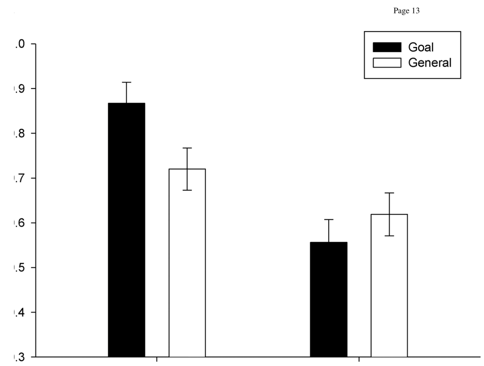
Hierarchical Bayesian modeling contributes to understanding temporal discounting by enabling better estimation in small samples through information sharing across individuals, enhancing parameter estimation robustness [32]. The two-stage analytical approach simplifies discounting rate quantification by first computing individual rates and then examining them across participant characteristics, providing insights into factors influencing discounting behavior [25]. This approach emphasizes the stable and heritable nature of temporal discounting and its associations with socio-economic status, personality traits, and cognitive abilities [33].

Future research should validate effective manipulations and explore delay discounting mechanisms, investigating the transference of training effects to real-world behaviors [30]. By examining various models and frameworks, researchers can deepen their understanding of temporal discounting intricacies and develop targeted interventions to promote healthier decision-making. Such efforts may yield more effective strategies that enhance self-control and reduce impulsive behaviors, ultimately contributing to improved health outcomes.

Figure 6 highlights the significance of temporal discounting in understanding cognitive behavior, especially in decision-making processes involving trade-offs between immediate and delayed rewards. The frameworks and models provide insights into prioritizing short-term gains over long-term benefits, analyzed through various experimental paradigms. The first example, "Reinforcement Learning in a Decision-Making Task," illustrates participants selecting between options with different reinforcement outcomes, highlighting the complexities of maximizing reward rates through strategic decision-making. The second example, "Goal vs. General: A Comparison of Performance in a Task," compares performance across varying task difficulties, enhancing understanding of cognitive mechanisms influencing temporal discounting and behavior across diverse contexts [36, 23].



(a) Reinforcement Learning in a Decision-Making Task[36]



(b) Goal vs. General: A Comparison of Performance in a Task[23]

Figure 6: Examples of Frameworks and Models of Temporal Discounting

6 Decision-Making Processes

6.1 Measurement and Methodological Advances

Benchmark	Size	Domain	Task Format	Metric
TD-AN-OCD-SAD[4]	196	Psychiatry	Temporal Discounting	Discount Rate, Discount Factor
MCQ-27[37]	680	Behavioral Economics	Delay Discounting	Test-retest reliability, Stability

Table 1: Table illustrating representative benchmarks in the study of temporal discounting across different domains. The table includes details on benchmark names, sample sizes, associated domains, task formats, and metrics used for assessment. These benchmarks provide a framework for understanding decision-making processes in various contexts, such as psychiatry and behavioral economics.

Recent methodological innovations in measuring decision-making processes, particularly regarding food choices, emphasize the role of individual differences in temporal discounting and their impact on dietary behaviors. The introduction of rapid assessment techniques enables frequent and non-intrusive measurements of delay discounting in natural environments, offering real-time insights into preferences for immediate versus delayed rewards [27, 12]. This advancement enhances our understanding of the behavioral economics underlying health-related decisions. Table 1 provides an overview of key benchmarks used to assess temporal discounting, highlighting their relevance in understanding decision-making processes across different domains.

Research into psychiatric conditions further illustrates temporal discounting's influence, highlighting the complexity of decision-making processes and the necessity for measurement approaches that account for psychological and cognitive variability [4]. By capturing these nuances, researchers can identify factors shaping food choices and develop targeted interventions to promote healthier dietary behaviors.

Training paradigms have been explored to modify decision-making processes. For instance, participants trained to respond quickly to food items under time constraints showed increased preferences for these items in subsequent choices, indicating that decision-making can be influenced through specific training interventions [20]. This suggests potential for encouraging healthier food choices.

These methodological advancements provide valuable insights into the cognitive and behavioral factors influencing dietary decisions. By employing rapid assessment techniques and innovative training paradigms, such as episodic future thinking (EFT) and mindfulness-based interventions, researchers can develop strategies to mitigate the effects of temporal discounting—a cognitive bias favoring immediate rewards—and promote healthier eating habits. These approaches not only reduce delay discounting but also enhance dietary decision-making, indicating their broader applicability in public health initiatives aimed at improving long-term health outcomes [27, 30, 28, 20, 22].

6.2 Measurement and Reliability of Delay Discounting

Advancements in the measurement and reliability of delay discounting are crucial for understanding decision-making processes, especially concerning impulsivity and self-control. The Adaptive Design Optimization (ADO) method significantly enhances measurement reliability, precision, and efficiency across diverse populations by optimizing experimental designs and reducing the number of trials necessary for accurate measurements [29].

Hierarchical Bayesian methods have improved the reliability of temporal discounting estimates, particularly in studies with small sample sizes, by facilitating information sharing across individuals. This enhances parameter estimation and provides a robust understanding of impulsivity, valuable in clinical contexts [32]. These methods address variability in discounting behavior and offer insights into the mechanisms underlying decision-making processes.

Quantitative models further enable the assessment of discounting rates through statistical comparisons across different participant demographics. Utilizing t-tests and regression analyses allows researchers to evaluate relationships and performance, providing a comprehensive framework for analyzing individual differences in temporal discounting [25]. These tools are crucial for understanding how demographic factors influence discounting behavior and for developing targeted interventions to promote healthier decision-making.

Recent methodological advancements in measuring delay discounting have enriched our understanding of the intricate interplay between cognitive and behavioral factors shaping decision-making processes. These improvements address earlier criticisms regarding the construct validity of delay discounting, which has shown only modest correlations with psychological dysfunction. By differentiating between the nuanced effects of various outcomes—such as monetary versus nonmonetary rewards—these advancements offer a more comprehensive framework for interpreting how delay discounting relates to maladaptive behaviors, including substance abuse and risky decision-making. This refined approach enables researchers to better assess the implications of delay discounting across diverse contexts, ultimately leading to more effective interventions and clinical applications [13, 34, 38]. By enhancing the reliability and precision of these assessments, researchers can further explore the complex interplay between impulsivity, self-control, and temporal preferences, contributing to the development of effective strategies for improving public health outcomes.

7 Interventions and Implications

7.1 Interventions and Behavioral Modification

Method Name	Intervention Techniques	Scalability and Accessibility	Cognitive and Behavioral Focus
OEFT[28]	Personalized Feedback	Online Delivery	Impulsive Decision-making
CMRM[14]	Personalized Feedback	Widely Implemented	Cognitive Processes
EF-DDA[1]	Behavioral Tasks	Widely Implemented	Cognitive Performance

Table 2: Overview of intervention methods for behavioral modification in obesity prevention, detailing the techniques employed, scalability, and cognitive focus. The table highlights the personalized feedback and behavioral tasks utilized in various methods, alongside their accessibility and impact on cognitive and behavioral processes.

Behavioral interventions are crucial for addressing obesity and encouraging healthier food choices. The MOFit framework exemplifies the integration of machine learning with real-time dietary tracking, providing personalized recommendations through tailored feedback and nudges, which enhance user engagement and promote healthier eating habits [11, 10]. Online episodic future thinking (OEFT) interventions offer scalable cognitive strategies that prioritize long-term rewards, broadening access and flexibility compared to traditional methods [28]. This scalability is vital for obesity prevention, allowing widespread implementation of cognitive strategies that enhance decision-making. Table 2 provides a comprehensive overview of various intervention methods aimed at behavioral modification in the context of obesity prevention, highlighting their techniques, scalability, and cognitive focus.

Social influences, particularly food choice mimicry, can facilitate healthier eating behaviors. Understanding mimicry dynamics within groups enables designing interventions that encourage individuals

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to adopt healthier dietary habits through peer influence [8]. Research highlights the effectiveness of subtle cues in guiding food choices, emphasizing significant determinants of dietary behavior [15].

Interventions targeting temporal discounting have shown promise, especially for individuals with anxiety disorders [4]. Future research should explore strategies that alter discounting behaviors to foster healthier decision-making [34]. The heritability and stability of temporal discounting, alongside associations with personality and cognitive variables, underscore the need for targeted interventions mitigating cognitive biases affecting dietary decisions [33].

Innovative training paradigms that influence impulsive food choices while preserving deliberative processes can enhance self-regulatory behaviors. These approaches consider age-related differences in delay of gratification and delay discounting, informing strategies to improve self-control and promote healthier eating habits [20, 39]. Future work could refine hierarchical models for impulsivity assessments and explore stress hormones' role in modifying impulsivity [32, 26]. The CMRM provides a nuanced analysis of complex interventions, accommodating diverse features and interactions overlooked by traditional methods [14]. Recommendations for O2O platforms include enhancing algorithms to promote healthier options and implementing clearer nutritional labeling [2]. Future research should investigate interventions targeting executive function to improve weight loss outcomes, including cognitive training programs [1]. Through these comprehensive approaches, behavioral interventions can effectively modify decision-making processes, enhancing public health outcomes.

7.2 Episodic Future Thinking (EFT) Interventions

Episodic Future Thinking (EFT) interventions are a promising strategy for reducing delay discounting (DD) and improving decision-making across various health behaviors. By mentally simulating future events, EFT increases the perceived value of delayed rewards, promoting long-term health benefits. Research demonstrates that EFT interventions significantly reduce impulsive decision-making, particularly in dietary choices and weight management, encouraging individuals to consider future outcomes even under time pressure [20, 27, 13].

EFT's effectiveness in reducing DD is particularly relevant for modifying behaviors linked to obesity and related health issues. By enhancing self-control in food choices, EFT encourages individuals to prioritize healthier options, leading to improved dietary decisions and more effective weight management outcomes. This intervention helps individuals resist immediate gratifications, promoting the selection of nutritious foods even amidst challenges like financial stress [20, 28].

Integrating acceptance-based and mindfulness-based trainings with EFT further enhances its effectiveness by fostering a balanced perspective on immediate versus delayed rewards [30]. This combination addresses the multifaceted nature of health-related decision-making.

EFT interventions can be effectively delivered through diverse formats, including online platforms, enhancing accessibility and scalability. This adaptability allows broader implementation in addressing public health challenges such as obesity, where EFT has shown promise in reducing delay discounting and improving choices, even in economically challenging contexts [28, 18]. The use of digital tools facilitates the dissemination of EFT strategies, reaching varied populations and enabling personalized interventions. Incorporating technology into EFT allows for real-time feedback and nudges that reinforce future-oriented thinking, promoting healthier lifestyle choices.

7.3 Technology-Driven Interventions

Technology-driven interventions are pivotal in facilitating behavioral modifications for addressing obesity and promoting healthier food choices. The integration of machine learning and predictive analytics into dietary interventions exemplifies technology's potential to personalize and enhance these strategies' effectiveness. For instance, the MOFit framework employs real-time dietary tracking and machine learning to provide tailored dietary recommendations, influencing food choices through personalized feedback and nudges [11].

The emergence of online-to-offline (O2O) food delivery platforms presents both challenges and opportunities for technology-driven interventions. While these platforms often prioritize convenience over nutritional value [2], they also present unique opportunities for promoting healthier options. Recommendations for O2O platforms include enhancing algorithms to prioritize nutritious choices and implementing clearer nutritional labeling to guide consumer decisions [2].

Furthermore, technology can effectively leverage social influences to encourage healthier eating behaviors. The dynamics of food choice mimicry observed in social settings can be harnessed through digital platforms to promote positive dietary changes [8]. Understanding mimicry mechanisms allows for interventions that capitalize on peer influence to foster healthier eating habits.

Persuasive visualizations and nudging strategies exemplify technology's role in facilitating interventions. By providing users with health information related to food choices, these tools reinforce cognitive shifts and promote healthier decision-making processes [10]. The integration of acceptance-based and mindfulness-based trainings with technology-driven interventions enhances their effectiveness by fostering a balanced perspective on immediate and delayed rewards [30].

Smart nudging systems utilizing machine learning and health guidelines from reputable organizations demonstrate significant potential for reshaping decision-making regarding food choices. These interventions not only facilitate healthier eating habits through persuasive visual cues and recommendations but also address challenges posed by online food delivery platforms that can lead to unhealthy choices. Research indicates that tailored nudges can increase the likelihood of selecting healthier recipes, while understanding the online food environment can mitigate risks associated with fast food consumption. Furthermore, training impulsive decision-making towards healthier food options suggests that dietary choices can be influenced through strategic cues, advocating for a multifaceted approach to promoting healthier lifestyles [20, 2, 10, 18]. By leveraging machine learning, predictive analytics, and digital platforms, these interventions can be tailored to individual needs and scaled to reach diverse populations, ultimately contributing to improved public health outcomes.

8 Conclusion

8.1 Future Research Directions

Future research should aim to broaden the scope of datasets to include a wider range of populations, thereby improving the applicability of dietary guidelines and interventions. Analyzing the long-term impacts of Online Episodic Future Thinking (OEFT), along with its demographic reach and incorporation into comprehensive health strategies, holds significant promise. Enhancing food choices and interventions in educational settings by leveraging insights from food choice mimicry studies can contribute to healthier eating patterns.

Developing robust models that encapsulate the complex interplay of physiological, psychological, and emotional determinants of food choices is crucial. Expanding theories like TIMERR to integrate additional decision-making elements could provide valuable clinical insights across diverse scenarios. Further, understanding genetic links to obesity, including gene-environment interactions, and focusing on varied populations will increase the relevance of genetic research outcomes.

Attention should also be directed towards younger age groups, employing longitudinal studies to gain insights into the evolution of self-regulation across different life stages. Examining the effectiveness of cue-approach training in diverse real-world contexts presents another fruitful research avenue. A comprehensive analysis that includes a wider array of covariates and interaction effects is essential to deepen our understanding of obesity interventions.

Investigating the neurobiological foundations of sex differences in impulsivity and expanding research to encompass diverse demographic groups are vital for future exploration. Delving into the neural underpinnings of temporal discounting in relation to anxiety, and exploring potential interventions to enhance decision-making related to food, are also imperative. Additionally, examining how genetic predispositions interact with environmental factors, especially the role of obesogens in metabolic dysfunction, should be prioritized.

Finally, advancing research in temporal discounting and decision-making processes will benefit from exploring new models for data analysis, refining methods for handling outliers, and assessing the broader implications of findings across various populations. These comprehensive research endeavors will pave the way for more effective strategies in combating obesity and encouraging healthier lifestyle choices.

References

[1] Fania CM Dassen, Katrijn Houben, Vanessa Allom, and Anita Jansen. Self-regulation and obesity: the role of executive function and delay discounting in the prediction of weight loss. *Journal of Behavioral Medicine*, 41:806–818, 2018.

[2] Yunke Zhang, Yiran Fan, Peijie Liu, Fengli Xu, and Yong Li. Cyber food swamps: Investigating the impacts of online-to-offline food delivery platforms on healthy food choices, 2024.

[3] Tao Ding, Warren K. Bickel, and Shimei Pan. $1 today or $2 tomorrow? the answer is in your facebook likes, 2017.

[4] Joanna E Steinglass, Karolina M Lempert, Tse-Hwei Choo, Marcia B Kimeldorf, Melanie Wall, B Timothy Walsh, Abby J Fyer, Franklin R Schneier, and H Blair Simpson. Temporal discounting across three psychiatric disorders: Anorexia nervosa, obsessive compulsive disorder, and social anxiety disorder. *Depression and anxiety*, 34(5):463–470, 2017.

[5] Jeffrey S Stein, William H Craft, Rocco A Paluch, Kirstin M Gatchalian, Mark H Greenawald, Teresa Quattrin, Lucy D Mastrandrea, Leonard H Epstein, and Warren K Bickel. Bleak present, bright future: Ii. combined effects of episodic future thinking and scarcity on delay discounting in adults at risk for type 2 diabetes. *Journal of behavioral medicine*, 44:222–230, 2021.

[6] Robert H Lustig, David Collier, Christopher Kassotis, Troy A Roepke, Min Ji Kim, Etienne Blanc, Robert Barouki, Amita Bansal, Matthew C Cave, Saurabh Chatterjee, et al. Obesity i: Overview and molecular and biochemical mechanisms. *Biochemical pharmacology*, 199:115012, 2022.

[7] Kristina Gligorić, Ryen W. White, Emre Kıcıman, Eric Horvitz, Arnaud Chiolero, and Robert West. Formation of social ties influences food choice: A campus-wide longitudinal study, 2021.

[8] Kristina Gligoric, Arnaud Chiolero, Emre Kıcıman, Ryen W. White, Eric Horvitz, and Robert West. Food choice mimicry on a large university campus, 2023.

[9] Tamara S Hannon and Silva A Arslanian. Obesity in adolescents. *New England Journal of Medicine*, 389(3):251–261, 2023.

[10] Mansura A Khan, Khalil Muhammad, Barry Smyth, and David Coyle. Investigating health-aware smart-nudging with machine learning to help people pursue healthier eating-habits, 2021.

[11] Satvik Garg and Pradyumn Pundir. Mofit: A framework to reduce obesity using machine learning and iot, 2021.

[12] Leonard H Epstein, Rocco A Paluch, Jeffrey S Stein, Teresa Quattrin, Lucy D Mastrandrea, Kyle A Bree, Yan Yan Sze, Mark H Greenawald, Mathew J Biondolillo, and Warren K Bickel. Delay discounting, glycemic regulation and health behaviors in adults with prediabetes. *Behavioral Medicine*, 47(3):194–204, 2021.

[13] Jillian M Rung and Gregory J Madden. Experimental reductions of delay discounting and impulsive choice: A systematic review and meta-analysis. *Journal of experimental psychology: general*, 147(9):1349, 2018.

[14] Annabel L Davies and Julian P T Higgins. A complex meta-regression model to identify effective features of interventions from multi-arm, multi-follow-up trials, 2024.

[15] Gareth Leng, Roger AH Adan, Michele Belot, Jeffrey M Brunstrom, Kees De Graaf, Suzanne L Dickson, Todd Hare, Silvia Maier, John Menzies, Hubert Preissl, et al. The determinants of food choice. *Proceedings of the Nutrition Society*, 76(3):316–327, 2017.

[16] Mark O Goodarzi. Genetics of obesity: what genetic association studies have taught us about the biology of obesity and its complications. *The lancet Diabetes & endocrinology*, 6(3):223–236, 2018.

[17] Matthias Blüher. Obesity: global epidemiology and pathogenesis. *Nature reviews endocrinology*, 15(5):288–298, 2019.

[18] George Shaw Jr. au2 and Amir Karami. Computational content analysis of negative tweets for obesity, diet, diabetes, and exercise, 2017.

[19] William A. Masters, Amelia B. Finaret, and Steven A. Block. The economics of malnutrition: Dietary transition and food system transformation, 2022.

[20] Harm Veling, Zhang Chen, Merel C Tombrock, Iris AM Verpaalen, Laura I Schmitz, Ap Dijksterhuis, and Rob W Holland. Training impulsive choices for healthy and sustainable food. *Journal of Experimental Psychology: Applied*, 23(2):204, 2017.

[21] Uli Bromberg, Maria Lobatcheva, and Jan Peters. Episodic future thinking reduces temporal discounting in healthy adolescents. *PLoS One*, 12(11):e0188079, 2017.

[22] Karolina M Lempert, Joanna E Steinglass, Anthony Pinto, Joseph W Kable, and Helen Blair Simpson. Can delay discounting deliver on the promise of rdoc? *Psychological medicine*, 49(2):190–199, 2019.

[23] Sara O'Donnell, Tinuke Oluyomi Daniel, and Leonard H Epstein. Does goal relevant episodic future thinking amplify the effect on delay discounting? *Consciousness and cognition*, 51:10–16, 2017.

[24] Jillian M Rung and Gregory J Madden. Demand characteristics in episodic future thinking ii: The role of cues and cue content in changing delay discounting. *Experimental and Clinical Psychopharmacology*, 27(5):482, 2019.

[25] Christopher T. Franck. Chapter 10: Quantitative models of discounting, 2024.

[26] Taiki Takahashi, Mizuho Shinada, Keigo Inukai, Shigehito Tanida, Chisato Takahashi, Nobuhiro Mifune, Haruto Takagishi, Yutaka Horita, Hirofumi Hashimoto, Kunihiro Yokota, Tatsuya Kameda, and Toshio Yamagishi. Stress hormones predict hyperbolic time-discount rates six months later in adults, 2011.

[27] Jeffrey S Stein, Yan Yan Sze, Liqa Athamneh, Mikhail N Koffarnus, Leonard H Epstein, and Warren K Bickel. Think fast: rapid assessment of the effects of episodic future thinking on delay discounting in overweight/obese participants. *Journal of Behavioral Medicine*, 40:832–838, 2017.

[28] Yan Yan Sze, Jeffrey S Stein, Warren K Bickel, Rocco A Paluch, and Leonard H Epstein. Bleak present, bright future: Online episodic future thinking, scarcity, delay discounting, and food demand. *Clinical Psychological Science*, 5(4):683–697, 2017.

[29] Woo-Young Ahn, Hairong Gu, Yitong Shen, Nathaniel Haines, Hunter A Hahn, Julie E Teater, Jay I Myung, and Mark A Pitt. Rapid, precise, and reliable measurement of delay discounting using a bayesian learning algorithm. *Scientific reports*, 10(1):12091, 2020.

[30] Hanneke Scholten, Anouk Scheres, Erik De Water, Uta Graf, Isabela Granic, and Maartje Luijten. Behavioral trainings and manipulations to reduce delay discounting: A systematic review. *Psychonomic bulletin & review*, 26:1803–1849, 2019.

[31] Trambak Bhattacharyya, Shanu Shukla, and Ranu Pandey. A tsallis-like effective exponential delay discounting model and its implications, 2023.

[32] M Fiona Molloy, Ricardo J Romeu, Peter D Kvam, Peter R Finn, Jerome Busemeyer, and Brandon M Turner. Hierarchies improve individual assessment of temporal discounting behavior. *Decision*, 7(3):212, 2020.

[33] Kristof Keidel, Qëndresa Rramani, Bernd Weber, Carsten Murawski, and Ulrich Ettinger. Individual differences in intertemporal choice. *Frontiers in psychology*, 12:643670, 2021.

[34] Amy L Odum, Ryan J Becker, Jeremy M Haynes, Ann Galizio, Charles CJ Frye, Haylee Downey, Jonathan E Friedel, and DM Perez. Delay discounting of different outcomes: Review and theory. *Journal of the experimental analysis of behavior*, 113(3):657–679, 2020.

[35] Liqa N Athamneh, Madison D Stein, Elysia H Lin, Jeffrey S Stein, Alexandra M Mellis, Kirstin M Gatchalian, Leonard H Epstein, and Warren K Bickel. Setting a goal could help you control: Comparing the effect of health goal versus general episodic future thinking on health behaviors among cigarette smokers and obese individuals. *Experimental and clinical psychopharmacology*, 29(1):59, 2021.

[36] Vijay Mohan K Namboodiri, Stefan Mihalas, Tanya Marton, and Marshall G Hussain Shuler. A general theory of intertemporal decision-making and the perception of time, 2013.

[37] Justin C Strickland, Brett W Gelino, Jill A Rabinowitz, Magdalene R Ford, Lauren Dayton, Carl Latkin, and Derek D Reed. Temporal reliability and stability of delay discounting: A 2-year repeated assessments study of the monetary choice questionnaire. *Experimental and clinical psychopharmacology*, 31(5):902, 2023.

[38] Allen J Bailey, Ricardo J Romeu, and Peter R Finn. The problems with delay discounting: A critical review of current practices and clinical applications. *Psychological Medicine*, 51(11):1799–1806, 2021.

[39] Lars M Göllner, Nicola Ballhausen, Matthias Kliegel, and Simon Forstmeier. Delay of gratification, delay discounting and their associations with age, episodic future thinking, and future time perspective. *Frontiers in psychology*, 8:2304, 2018.

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