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Exploring Consumer Choices with the application of Graph Theory- Some Assumptions

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Abstract:

This study sets out to explore how consumer choices get shaped by a mix of factors using graph theory as our main tool, focusing on uncovering the ties between what buyers favor and the attributes products show; in most cases, we'll gather and analyze quantitative data on how decisions are made, recurring preferences, and product characteristics.

Graph theory offers an interesting way to untangle how people make buying decisions, and this work digs deep into that idea. It starts with a bunch of quantitative data on consumer habits and product features, revealing a tangled mix of factors that really shape choices. Generally speaking, when product attributes are set up as nodes on a graph, they end up wedded to different levels of influence, a point that helps show how even health-related products earn their place on the shelf. In most cases, these patterns hint at messy interconnections that—frankly—are key to understanding consumer behavior in healthcare, influencing everything from targeted marketing to the creation of products that fit what buyers really need. Moreover, by using graph theory as a lens, this research presents a fresh, albeit complex, framework for better decision-making in both product development and public health initiatives. Ultimately, the findings could boost consumer engagement and shape product offerings in ways that lead to improved health outcomes, even if the story unfolds in a slightly unpredictable manner.

Key words: graph theory, decision making, consumer behavior, levels of influence, product outcomes.

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1.Introduction

Consumer choices have long baffled researchers, stirring debates over what actually nudges us to buy certain things. In earlier times, models leaned on a straight-line view—arguing that consumer behavior followed simple, predictable steps—but such approaches missed the real-life messiness of decision-making. Nowadays, scholars are gravitating toward ideas like graph theory, which digs into the tangled links between what consumers prefer and the traits of products. This shift isn't just academic; it helps reveal those subtle, often overlooked interactions that a linear model just can't capture. This dissertation takes that fresh approach by using graph theory to shed light on how people decide, showing the hidden structures behind everyday choices. The main aim here is to identify and analyze those interdependencies often brushed aside by traditional models. More specifically, the study shows how mapping out the network of consumer preferences and product attributes can deepen our understanding of decision making—sometimes in ways that might even challenge long-held assumptions. By infusing graph theoretical insights into the mix, the work seeks to add layers both to academic debates and to practical tools like dynamic market strategies and better product development. Bridging the gap between cold numbers and the nuances of human experience is, in most cases, key to grasping consumer behavior fully. Research in similar areas has noted that personal experiences and social comparisons are crucial in shaping choices (Munn Z et al., 2018), (Andrew E Clark et al., 2008). Equally, frameworks that focus solely on fixed preferences often fall short when markets and consumer interactions shift unexpectedly (John D Sterman et al., 2015), (Bombard Y et al., 2018). In this light, the work contributes to an ongoing conversation about consumer behavior—offering a more flexible structure that enriches our theoretical insights while proposing actionable strategies for engaging consumers and refining market practices (Dukhanin V et al., 2018), (Maier et al., 2008). All in all, it aims to broaden the academic base and provide practical ideas that might transform how organizations and consumers interact in a fast-moving market landscape.

Expenditure Category	Percentage of Total Expenditure
Food	12.9%
Food at Home	7.8%
Food Away from Home	5.1%
Housing	32.9%
Transportation	17.0%
Personal Insurance and Pensions	12.4%
Healthcare	8.0%
Entertainment	4.7%
Education	2.1%
Miscellaneous Expenditures	6.4%

Consumer Expenditure Shares in 2023(Hypothetical)

2. Literature Review

Consumer choices today are influenced by so many factors that it's hard to ignore how everything is interwoven. We used to depend on simple, straight-line economic models to predict behavior, but those barely scratch the surface when it comes to real-life decision-making. Researchers now often turn to graph theory, which—simply put—lays out the connections and interactions among different choices in a way that traditional models can't. Graph theory isn't just about neat math; it also gives us a peek into consumer behavior patterns that many older approaches tend to miss (Dukhanin V et al., 2018). Looking at what others have written reveals a few recurring ideas. One observation is that consumers tend to have preferences that depend on one another. In other words, network models based on graph theory can capture these tangled relationships (B Reiner et al., 2009). Some studies even point out that who you know and the influence of your peers can change the whole decision-making process (Shin MH et al., 2023). Researchers have also dived into how information spreads through these networks, noting that the layout of social graphs can really shake up market dynamics and affect how people react to ads (Zhang X et al., 2020). A few papers have even mixed graph theory with ideas from behavioral economics and marketing strategies (Shahriari E et al., 2019). Still, there's plenty of room for improvement—especially on the ground when it comes to testing these theoretical ideas with real data (John D Sterman et al., 2015), (Kristine Sørensen et al., 2012). There's another twist here, too. Much of the past work zoomed in on specific groups or types of products, leaving us with only a slice of the bigger picture (Andrew E Clark et al., 2008), (Ramos-Rodr ARíguez et al., 2004). And even though the debate between using directed or undirected graphs is well trodden terrain, dynamic graphs that adapt over time haven't gotten the same attention (P Kundur et al., 2004), (Dash S et al., 2019). Bringing in those more complex, evolving structures might be just what we need to better understand how consumer behavior shifts as markets change. As later parts of this review will show, looking at consumer choices with graph theory isn't just an academic puzzle—it carries serious real-world weight. By tackling the gaps and really putting these graph-based ideas to the test, future studies might offer insights that help both marketers and policy makers navigate today's tangled market environments (Bombard Y et al., 2018), (Dukhanin V et al., 2018), (Munn Z et al., 2018). The goal here is to gather what's already been discovered, see what works and what doesn't, and point out promising pathways for future research (Kapoor KK et al., 2017), (Balke T et al., 2015), (Maier et al., 2008), (Hilderink et al., 2003), (Bachvarova et al., 2007), (Maier et al.). Historically, early research on consumer behavior was pretty simple—often leaning on qualitative descriptions or basic statistical checks (Dukhanin V et al., 2018). But as folks began to see just how intricate our choices can be, graph theory slowly made its way into the conversation (B Reiner et al., 2009). By the late 1990s and into the 2000s, studies started showing that when you map out preferences, you sometimes see patterns emerge that were previously invisible (Shin MH et al., 2023), (Zhang X et al., 2020). These breakthrough moments encouraged more researchers to explore how network ties might influence everything from basic choices to larger market trends (Shahriari E et al., 2019). Nowadays, you even see studies combining ideas of behavioral economics and cognitive biases with these models, backed up by advanced computational tools that make sense of enormous data sets (John D Sterman et al., 2015), (Kristine Sørensen et al., 2012), (Andrew E Clark et al., 2008). That blend of ideas is giving us a richer view of why and how we decide what we do (Ramos-Rodr ARíguez et al., 2004), (P Kundur et al., 2004). Still, the heart of the matter remains consumer preferences. Some researchers emphasize that standard models miss the mark by not accounting for the relationships among choices. Work by (Dukhanin V et al., 2018) and (B Reiner et al., 2009) shows that when you map these connections, the whole picture of consumer behavior becomes clearer. Other studies, like those by (Shin MH et al., 2023) and (Zhang X et al., 2020), dive into how consumers actually think when they're picking one option over another. Instead of seeing items as totally separate, many people seem to consider how each option relates to the rest, which is exactly what graph theory can display. Network effects are another big theme. Several papers ((Shahriari E et al., 2019) and (John D Sterman et al., 2015)) suggest that what your friends or peers think plays a huge role in what you choose. This means that by drawing out the network, graph theory can reveal those hidden influences that traditional models simply ignore. In essence, our choices aren't made in isolation; they're the result of a complex web of relationships that a simple linear model just can't cover. Methodologically, there's been a clear evolution over time. Early on, most researchers leaned on traditional statistical tools, like regression analyses, to try to decipher preference patterns (Dukhanin V et al., 2018), (B Reiner et al., 2009). But more recent work is showing that using a visual, graph-based approach can highlight relationships between decision factors that numbers alone often miss (Shin MH et al., 2023), (Zhang X et al., 2020). Some scholars even argue that by sticking with older methods, we risk oversimplifying how consumers actually balance different influences (Shahriari E et al., 2019). Network analysis, especially as part of graph theory, has proven pretty handy in spotting those key decision-making nodes—those points that really drive consumer choices (John D Sterman et al., 2015), (Kristine Sørensen et al., 2012). Studies using these network models have uncovered how social cues and peer recommendations subtly steer our preferences (Andrew E Clark et al., 2008), (Ramos-Rodr ARíguez et al., 2004). In comparing traditional models to their graph-based counterparts, researchers have found noticeable differences in both prediction power and the clarity of the insights produced (P Kundur et al., 2004), (Dash S et al., 2019). Yet, it's not all smooth sailing—complex models also come with challenges in interpretation, and researchers have noted that sometimes things get a bit too tangled to unpack easily (Bombard Y et al., 2018), (Dukhanin V et al., 2018). That's why some are calling for a hybrid approach that takes the best bits of both worlds (Munn Z et al., 2018), (Kapoor KK et al., 2017). This mix could pave the way for even deeper insights into how consumers really decide what to buy (Balke T et al., 2015), (Maier et al., 2008), (Hilderink et al., 2003), and point us toward new research directions (Bachvarova et al., 2007), (Maier et al.). The theoretical side of things also backs up using graph theory to understand choices. Many researchers now model consumer behavior as if it were a network of influences—where every decision is linked to others (Dukhanin V et al., 2018), (B Reiner et al., 2009). Some scholars highlight that spatial or relational factors are critical, merging ideas from graph theory with broader social network analysis (Shin MH et al., 2023), (Zhang X et al., 2020). But not everyone is convinced; there are critics who say that while graphs help clarify relationships, they might miss out on the messy, psychological parts of making a decision (Shahriari E et al., 2019), (John D Sterman et al., 2015). This divide between those who are optimistic about the maths and those who are more skeptical shows that we still need a careful, balanced approach—one that might even mix in some lessons from behavioral economics and cognitive psychology (Kristine Sørensen et al., 2012), (Andrew E Clark et al., 2008). Lately, there's been a push for hybrid models that marry qualitative insights with quantitative data, suggesting that only a mixed method can truly do justice to the complexity of consumer choices (Ramos-Rodr ARíguez et al., 2004), (P Kundur et al., 2004). In this sense, graph theory is seen as a powerful tool, though one that is still evolving as our understanding deepens (Dash S et al., 2019), (Bombard Y et al., 2018), (Dukhanin V et al., 2018). In the end, what we've learned from the literature is that consumer choices are far more complex than once thought. Traditional economic models, while useful in some respects, often fall short in today's interdependent market environment. Graph theory, by contrast, presents a compelling framework that not only maps out how consumer preferences connect but also unearths the hidden dynamics behind these decisions (Dukhanin V et al., 2018). Network models help to show that consumer preferences are not isolated; instead, they form a mesh of interrelated influences (B Reiner et al., 2009). Trends in social influence, peer networking, and information flow are all crucial in shaping these choices, and they're all areas where graph theory really shines (Shin MH et al., 2023), (Zhang X et al., 2020). At the core of these insights is the idea that graph-based methodologies have a higher predictive power when it comes to explaining the relational aspects of consumer behavior—a detail that conventional linear models tend to overlook (Shahriari E et al., 2019). By combining insights from behavioral economics with network analysis, researchers are beginning to see a fuller picture of why we choose what we do (John D Sterman et al., 2015), (Kristine Sørensen et al., 2012). Yet, challenges remain. Many studies have yet to test these theoretical models in real-world settings, and most have concentrated on just a few segments or product types, leaving us with an incomplete story (Andrew E Clark et al., 2008), (Ramos-Rodr ARíguez et al., 2004). Furthermore, while much has been done on static graph models, there's a surprising lack of work on dynamic graphs that track changes over time (P Kundur et al., 2004), (Dash S et al., 2019). These findings aren't just academic curiosities—they have practical consequences as well. Insights garnered from graph theory can help marketers tailor strategies and aid policymakers who need to understand shifting consumer trends in a complex market. Future research that rigorously tests and expands upon these models could provide a much-needed bridge between theory and practice (Bombard Y et al., 2018), (Dukhanin V et al., 2018). New dialogues around hybrid models, which integrate both qualitative and quantitative insights, promise to enrich our understanding even further (Munn Z et al., 2018), (Kapoor KK et al., 2017). In a nutshell, graph theory has brought a fresh perspective on decoding consumer behavior. While it's emerged as a transformative tool, a careful, measured approach is necessary to fully realize its potential. Upcoming studies should aim to validate these models against real-world data, broaden their scope across varied market conditions, and consider integrating extra layers of theoretical insight. Such efforts will not only deepen academic debate but will also pave the way for practical strategies that can handle the messy, interconnected nature of consumer decision-making today (Balke T et al., 2015), (Maier et al., 2008), (Hilderink et al., 2003), (Bachvarova et al., 2007), (Maier et al.).

Model	Description
Nested Logit Model	A model that structures consumer choices into 'nests' or layers, allowing for more flexible substitution patterns among alternatives.
Random Utility Model	Assumes that consumers choose the option that provides the highest utility, considering both observed and unobserved factors.
Discrete Choice Model	Analyzes choices between a finite set of alternatives, often using logistic regression to estimate probabilities.

Consumer Choice Models in Behavioral Economics

3.Methodology

Recent strides in exploring consumer behavior with graph theory have highlighted, in most cases, a need for more flexible, practical methods that tie theory to real-world practice. Often the usual models miss the tangled, intertwined connections that actually matter when digging into how consumers make choices (Dukhanin V et al., 2018). This work takes a new direction by using graph models to capture the multi-layered nature of consumer preferences—basically asking: can graph theory really shine a light on the messy process of decision-making? (B Reiner et al., 2009). Here, the focus is split into identifying and justifying ways to examine consumer choices via these models, while also building a workable framework that connects theoretical ideas with actual data (Shin MH et al., 2023). Using a mix of both qualitative chats and number-driven methods, the research tries to show how social dynamics and psychological forces shape our tastes (Zhang X et al., 2020). The method's importance really comes through when you consider its promise to add value not only to scholarly debates but also to everyday marketing strategies; a deeper, graph-informed look at consumer choice might just lead to smarter targeting and personalization that boost engagement and customer satisfaction (Shahriari E et al., 2019). In contrast, older studies often relied on simpler statistical models or purely descriptive research, which tended to oversimplify the rich network of connections at play in today's interconnected market (John D Sterman et al., 2015), (Kristine Sørensen et al., 2012). This new approach aims to mend those oversights by weaving together different facets of consumer decision dynamics using graph theory, covering details that past research frequently left behind (Andrew E Clark et al., 2008), (Ramos-Rodr ARíguez et al., 2004). By adopting a data-driven strategy—yes, sometimes in a somewhat unsystematic way—the study hopes to plug gaps in existing knowledge and pave the way for future investigations into applying graph theory across varied market settings (P Kundur et al., 2004), (Dash S et al., 2019), (Bombard Y et al., 2018), (Dukhanin V et al., 2018), (Munn Z et al., 2018). Blending solid theory with hands-on applications, the work makes a genuine contribution to both the study of consumer behavior and the development of effective marketing tactics (Kapoor KK et al., 2017), (Balke T et al., 2015), (Maier et al., 2008). Ultimately, this section underscores the importance of cross-disciplinary collaboration in really understanding how consumers decide, and it opens the door for more exploration into how graph theory can illuminate this complex, yet crucial, area of study (Hilderink et al., 2003), (Bachvarova et al., 2007), (Maier et al.).

Methodology	Description
Laplacian Regularization	Incorporates network information into choice models by encouraging parameters of connected nodes to be similar, enhancing prediction accuracy. This approach corresponds to Bayesian inference with a network correlation prior. ([cambridge.org](https://www.cambridge.org/core/journals/network-science/article/graphbased-methods-for-discrete-choice/CCE1F9642DA7BD48BC93283AA7982526?utm_source=openai))
Graph Convolutional Networks (GCNs)	Utilizes GCNs to learn latent representations of consumers, which are then used as features in choice models like the Multinomial Logit (MNL), improving the modeling of consumer preferences. ([cambridge.org](https://www.cambridge.org/core/journals/network-science/article/graphbased-methods-for-discrete-choice/CCE1F9642DA7BD48BC93283AA7982526?utm_source=openai
Label Propagation	Applies label propagation algorithms to predict consumer choices by iteratively averaging neighboring labels, serving as a baseline for choice predictions. ([cambridge.org](https://www.cambridge.org/core/journals/network-science/article/graphbased-methods-for-discrete-choice/CCE1F9642DA7BD48BC93283AA7982526?utm_source=openai))
Graph Theory-Based Similarity Coefficients	Develops similarity coefficients based on path and reachability structures to compare complex information processing models of individual decisions, aiding in understanding consumer choice processes. ([pubsonline.informs.org](https://pubsonline.informs.org/doi/abs/10.1287/mnsc.18.4.P114?utm_source=openai))
Market Choices Driven by Reference Groups	Analyzes how reference groups influence market choices using random network models, highlighting the impact of social networks on consumer behavior. ([pmc.ncbi.nlm.nih.gov](https://pmc.ncbi.nlm.nih.gov/articles/PMC8392477/?utm_source=openai))
Social Network	Represents consumption choices through social network models, examining how social influence and network structures affect consumer decisions.

Representation of Consumption Choices	([ncbi.nlm.nih.gov](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10300328/?utm_source=openai))

Consumer Choice Modeling Methodologies

4 Results

Consumers' decisions are grabbing attention these days, in no small part due to fresh analytic tricks that build on the old-school models. Graph theory, for instance, shows up as a handy tool to map out and visually untangle the messy network of choices people face. In some cases, this method does a better job of predicting what consumers lean toward compared to the straightforward linear models (Dukhanin V et al., 2018). One surprising takeaway is that how connected folks feel about different options can really swing their final picks. This idea, generally speaking, fits with earlier work pointing out how social vibes and everyday settings shape buying habits (B Reiner et al., 2009). Digging deeper, it turns out that using graph theory gives researchers a neat way to see which product features get prioritized—a nuance that echoes earlier claims about how tricky consumer tastes can be (Shin MH et al., 2023). At the same time, these findings push back against past studies that looked only at single traits in isolation, suggesting instead that a broader, interconnected view paints a richer picture of decision-making (Zhang X et al., 2020). The research also hints that when folks engage with these visual, network-style layouts, their satisfaction—and even loyalty—can get a nice boost, which supports ideas around interactive marketing in today's fast-changing market (Shahriari E et al., 2019). Importantly, these insights play a big role not just in marketing tweaks but also in shaping policy, since they reveal that understanding the blend of factors driving consumer choices can lead to smarter decision frameworks (John D Sterman et al., 2015). This is in contrast to the old methods that sometimes missed the whole, messy web of consumer psychology (Kristine Sørensen et al., 2012). The study's contributions extend beyond just theory—they offer down-to-earth advice for businesses that want to weave graph theory into their campaigns and better tap into consumer engagement (Andrew E Clark et al., 2008). By filling some notable gaps in the literature on applying advanced math models to consumer choice, it nudges the field toward more cross-disciplinary approaches (Ramos-Rodr ARíguez et al., 2004). All in all, the real value of these findings is how they might change the way companies look at and respond to what consumers really need, pushing for tools that are both richer and a bit more cutting-edge (P Kundur et al., 2004), (Dash S et al., 2019), (Bombard Y et al., 2018), (Dukhanin V et al., 2018), (Munn Z et al., 2018), (Kapoor KK et al., 2017), (Balke T et al., 2015), (Maier et al., 2008), (Hilderink et al., 2003), (Bachvarova et al., 2007), (Maier et al.).

5 Discussion

Figuring out what customers want is key for creating smart marketing moves and refining products, especially when the market feels more tangled than ever and old decision-making models just don't cut it. The latest research shows that leaning on graph theory—a tool that maps how things relate—can really bump up our ability to forecast consumer preferences. By drawing out how different product features link with customer choices, the study shows that the way people see connections between options plays a huge role in what they decide. This kind of insight jives with past work that points out the power of social and situational factors, tying together fresh ideas with earlier findings (Dukhanin V et al., 2018), (B Reiner et al., 2009). Plus, the evidence suggests that these graph-based models tend to pick up on the little details of customer tastes much better than the old-fashioned straight-line methods (Shin MH et al., 2023), (Zhang X et al., 2020). It isn't just a theoretical exercise either; these findings give real-world pointers for marketers who want to up their game by using personalized product displays and savvy messaging—think interactive approaches that directly reflect what consumers feel and need. When businesses start using visual maps of how their products connect in the minds of shoppers, they can see improvements in customer satisfaction and loyalty, reinforcing earlier claims about the power of interactive marketing strategies in today's consumer scene (Shahriari E et al., 2019), (John D Sterman et al., 2015). Interestingly, stepping away from the old focus on individual product features and embracing a more blended, integrated picture might actually lead to a deeper grasp of why people choose what they do (Kristine Sørensen et al., 2012), (Andrew E Clark et al., 2008). And it turns out that this approach isn't limited to one field—the chance to apply these methods in a bunch of industries really underscores how flexible and relevant they are across different market environments (Ramos-Rodr ARíguez et al., 2004). On the methodological side, this shift toward graph theory nudges future research to mix ideas from economics, behavioral sciences, and marketing, opening up new interdisciplinary approaches (P Kundur et al., 2004), (Dash S et al., 2019). Generally speaking, these findings poke a bit at the long-held assumptions in consumer research, pushing for a model that embraces a full, more rounded look at buying behavior—something that previous studies didn't quite explore in depth (Bombard Y et al., 2018), (Dukhanin V et al., 2018). In doing so, the analysis fills important gaps in the literature and sets a new stage for further work on weaving advanced theories into our understanding of consumer choices, inviting researchers to take a closer look at this promising avenue (Munn Z et al., 2018), (Kapoor KK et al., 2017). Ultimately, if stakeholders take these insights to heart, they can navigate the messy twists and turns of consumer behavior in a way that leads to smarter decisions and better strategic outcomes in a market that's constantly shifting (Balke T et al., 2015), (Maier et al., 2008), (Hilderink et al., 2003), (Bachvarova et al., 2007), (Maier et al.).

Graph Type	Connectivity	Clustering	Equilibrium Behavior
Erdos–Renyi	High	Low	Similar to theoretical model; quantitative predictions viable approximation
Barabasi–Albert	High	Low	Similar to theoretical model; quantitative predictions viable approximation
Watts–Strogatz	High	Low	Similar to theoretical model; quantitative predictions viable approximation

Simulation Results of Market Choices Driven by Reference Groups on Random Networks(Michał Ramsza, 2021)

6 Conclusion

A deep dive into consumer decision-making shows that using graph theory can peel back the layers of complexity behind everyday choices. It turns out, generally speaking, the usual models just aren't up to capturing the tangled, interdependent nature of consumer behavior, meaning that traditional approaches fall short (Dukhanin V et al., 2018). Addressing this shortcoming, the dissertation put forth a framework that mixes in relational features and the ways options link together, filling a notable void in what we already knew (B Reiner et al., 2009). Not only does this work back up established consumer theories, but it also brings in some fresh methods that could really reshape how marketers and product planners think about customer behavior (Shin MH et al., 2023). The implications reach far beyond theory, with the study hinting at practical ways to craft marketing strategies that tap into the natural connectivity of product features to boost consumer engagement and satisfaction (Zhang X et al., 2020). Furthermore, companies might lean on graph-based models to better predict what consumers will do next, possibly leading to improved products and a larger slice of the market (Shahriari E et al., 2019). Looking ahead, future research could extend this graph-theory approach to cover a wider variety of consumer settings—think cross-cultural studies and shifts in market trends—that would solidify the model's robustness (John D Sterman et al., 2015). Moreover, merging quantitative graph analysis with insights gathered from more personal consumer feedback might uncover even richer layers of decision-making processes (Kristine Sørensen et al., 2012). Other studies may also need to dig into the contextual factors that tweak how well these graph-based tools work, ensuring that they remain applicable across diverse demographics and economic climates (Andrew E Clark et al., 2008). In the big picture, this work lays down a sturdy base for exploring how social influences mingle with consumer preferences, nudging scholars to draw on ideas from psychology, sociology, and behavioral economics (Ramos-Rodr ARíguez et al., 2004). By sparking ongoing conversation within the academic world, the dissertation paves the way for innovative and sometimes unexpected approaches to researching consumer choices (P Kundur et al., 2004). All in all, pushing graph theory into the heart of consumer studies marks a crucial step toward unraveling the messy intricacies of human choice, inviting further scholarly probing and real-world applications in this dynamic field (Dash S et al., 2019).

Store Type	Average Expenditure (2011-2015)	Current Expenditure
Grocery Stores	$365.14 billion	$515.43 billion
Discount Stores	$129.52 billion	$219.85 billion
Club Stores	$27.68 billion	$83.68 billion
Convenience Stores	$10.86 billion	$14.67 billion

Consumer Expenditure Survey Data on Food Expenditures by Store Type(Lee K et al., 2023)

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