The Diderot effect: a data-driven validation

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THE DIDEROT EFFECT: A DATA-DRIVEN VALIDATION

ABSTRACT

Although it is theorized that consumer decisions are commonly irrational and based on systematic biases, there remains a need for more data-driven research to validate and expand upon these assumptions fully. This study is one of the few that, based on analysis and interpretation of complex data instead of qualitative methods, validates one of those biases, the Diderot effect. This study presents a conceptual model and a pioneering research approach combining indirect data and machine learning techniques to validate the manifestation of the Diderot effect on the purchase process of products of a specific category through an online retailer. Results showed that a laptop computer could be one of those products and that consumers might be more predisposed to making unforeseen purchases when they are already in a spending mindset. The findings highlight opportunities for marketing professionals to leverage the Diderot effect, creating value for consumers and organizations.

Keywords

Diderot effect; Consumer Buying Behavior; Complementary Products; Generalized Sequential Pattern Algorithm; Biases; Machine Learning.

INTRODUCTION

Consumption is a principal driving force behind social and economic development (Warde, 2014). While people's consumption behavior is often perceived as a rational decision-making process, the reality is quite different. Social norms, cultural traditions, habits, and many other factors shape our everyday consumption behavior (Power and Mount, 2010). Some authors argue that 95 percent of purchase decision-making occurs subconsciously (Zaltman, 2007). There are many reasons to rely on our subconscious for these decisions, such as information and choice overload, time constraints, or convenience (Willman-Iivarinen, 2017). Due to limited cognitive abilities and the desire to lower decision-making costs, individuals often rely on heuristics, mental shortcuts, and biases to make intuitive or automatic decisions. Additionally, the meaning we attach to products contributes to erratic human purchasing behavior. Consumption is more than satisfying physical needs; it can also be seen as a tool for self-branding and value signaling (Willman-Iivarinen, 2017).

The "Diderot effect," as conceptualized by McCracken (1990), delineates a cultural and psychological phenomenon whereby acquiring a single product disrupts an individual's established consumption patterns, initiating a sequence of complementary purchases to achieve congruence among possessions. This disruption arises when the new product, such as an expensive gift or a luxury product, introduces a level of quality, aesthetic sophistication, or symbolic status incongruent with the individual's existing possessions. Consequently, the consumer undertakes a reconfiguration of their material environment to align with the standards established by the new acquisition. McCracken identifies this initiating product as a "departure purchase" as it signifies a deviation from the consumer's prior behavioral and material patterns, catalyzing subsequent adjustments to their broader consumption framework (Lorenzen, 2015).

Building on the conceptual framework of the Diderot effect, supplementary acquisitions triggered by the "departure purchase" can be categorized into two overarching types: proximal and distal possessions. Proximal possessions are those that maintain a direct functional, aesthetic, or utilitarian connection to the initial product. These acquisitions enhance the new item's integration, utility, or visual coherence within the consumer's existing material environment, ensuring a seamless transition between the old and new consumption patterns (Belk, 1988). In contrast, distal possessions are not functionally connected to the initial acquisition but are instead acquired to establish a broader aesthetic or symbolic alignment. Such items may encompass furnishings, decorative elements, or other possessions that reflect the elevated quality or symbolic value introduced by the initial purchase.

In recent years, the availability of extensive online and offline consumer data has allowed organizations to understand their customers' preferences and behavior better. The advent of new data sources, such as online retailers, social networks, or search engines, has shifted the perspective of marketing from a descriptive discipline into a more predictive science (Sheth and Kellstadt, 2021). As a result, organizations, even unknowingly, can now take advantage of the Diderot effect through cross-selling and bundling strategies or delivery fulfillment tactics to boost average order values. This phenomenon can also be intentionally leveraged in marketing communications, mainly through personalized marketing, where businesses can use predictive analytics to identify patterns of complementary purchases and target consumers with highly relevant offers. Moreover, these insights can inform segmentation and targeting strategies, enabling companies to classify consumers based on their propensity to engage in cascading purchasing behavior. This can then be used to optimize promotional efforts and loyalty programs. Additionally, more sophisticated recommendation systems (Bansal and Baliyan, 2019) and innovations in developing new products that align more closely with customer needs and demands (Niu and Dai, 2022) are being introduced.

The Diderot effect can have many ramifications in today's world. Economically, one can think about how it influences rising levels of household debt in Western societies. On the environmental front, it raises questions about its impact on the demand for new products and purchase decisions (Gupta and Ogden, 2009). Anthropologically, it might be helpful to understand its influence on the constant generation of needs that could put consumers at financial risk and diminish well-being (Schor, 1999).

This research study aims to validate the influence of the Diderot effect on consumers' purchase behavior through a data-driven approach. Specifically, we explore how acquiring products that disrupt typical buying patterns may lead to quantifiable impacts on consumers' purchasing patterns. The focus is identifying the most common complementary products that become integral to the Diderot unity. Additionally, we investigate the ultimate cost of the entire ensemble of products, providing insights into the financial implications of the Diderot effect on consumer spending.

As far as the authors know, this is the first study to understand the Diderot effect through a data-driven approach. This approach uses complex data instead of observations or qualitative research methods, allowing for higher reproducibility and a larger randomized data collection (Ahmed et al., 2019) based on actual consumer behavior rather than self-reported actions or controlled settings. Additionally, this research would be able to analyze specific attributes of a consumer's purchase and thus provide insights that tentatively establish a benchmark for how this effect tends to operate. In essence, adopting a data-driven approach to researching this effect can advance the scientific foundations of behavioral economics, offering researchers, policymakers, and businesses a more empirically grounded and replicable understanding of the dynamics of consumer decision-making.

From another perspective, due to the infrequent availability of companies' transactional databases for independent academic studies, this research also aims to highlight the value of openly available data sources. In this case, reviews from an online retailer serve as a proxy for transactional databases, a novel approach in using online reviews that can have multiple applications in academic research. Therefore, it can be said that the study also seeks to confirm the value of customer reviews as a quantitative data source, potentially opening the door to new studies that were previously unviable.

LITERATURE REVIEW

REASONS FOR CONSUMPTION

Much has been studied and written about the psychological reasons behind consumption. People tend to buy products for their practical value and the meaning they bring to their lives (Belk, 1978). The literature states that one of the strongest cultural universals affecting consumer behavior is the belief that a person's possessions and expenditures reveal something about them.

People assign meaning to their purchases based on how they identify with them and how these items fit their lifestyle (Solomon, 1983). In this study, the author argues that the experience of consuming certain products promotes the "consumer's structuring of social reality." People try to communicate a desired social role by consuming complementary products. These consumption experiences are often interdependent; one purchase may lead to another, resulting in a consumption chain (Park, 2012).

In this context, impulse purchases, as Rook and Fisher (1995) note, represent spontaneous expressions of consumer behavior triggered by emotional and situational cues. These impulsive buying decisions are often influenced by the same desire for self-expression and social signaling observed in planned purchases. Studies assert that impulse buying embodies a multifaceted and swift process characterized by hedonic gratification, which often overrides the deliberative analysis of choices and their associated consequences, and people exhibiting impulsive buying tendencies are typically more emotionally driven than their more deliberative counterparts in traditional shopping contexts (Lo *et al.,* 2022).

Online vendors provide easy access to a wide range of products through digital shopping platforms, facilitating the accumulation of possessions (Ozimek et al., 2024). Studies have shown that online shoppers are more impulsive than their offline counterparts (Liu *et al.,* 2013). Additionally, e-commerce sales are rising, projected to reach 25% of global retail sales by 2027, up from 19% in 2022 (Coppola, 2023). Verhagen and van Dolen's (2011) study shows that impulse purchasing occurs in about 40% of all online expenditures.

While extensive research exists on various aspects of consumer purchasing behavior, such as initial purchase behavior, more literature is needed to explore the causes of subsequent purchases, such as the Diderot effect.

THE DIDEROT EFFECT

The eighteenth-century French philosopher Diderot (1789) was one of the first to document that "unity links consumer products in any complement, " meaning that consumers naturally seek harmony and coherence among their possessions. In other words, consumers tend to desire products that complement each other aesthetically, functionally, or symbolically, creating a sense of unity within their collections of belongings. Diderot himself was someone who had no interest in material goods. Later in his life, that changed when he was offered a brand new and luxurious robe. Soon after, he realized that none of his possessions matched the magnificence of this item. Therefore, Diderot quickly focused on establishing a new coherence based on the recent item by acquiring a new leather chair, then an opulent mirror over his fireplace, and later a new extravagant desk for his dressing room. Finally, Diderot reckons the robe "forced everything to conform with its elegant tone."

Based on this essay, the idea that possessions tend to have an internal consistency was further explored by McCracken (1990), who described this consistency of consumer products as "Diderot Unities." Other researchers have named a similar concept of product grouping "consumption constellations" (Solomon and Assael, 1987). Consumption constellations are groups of symbolic, complementary products, specific brands, and consumption activities that consumers use to define, communicate, and enact social roles (Solomon and Assael, 1987). Hence, a "Diderot unity" can be synonymous with a "consumption constellation."

McCracken (1990) describes how "Diderot unities" might be broken by introducing a new product that does not match the previous purchase pattern. Inspired by Diderot (Park, 2012), the author called this phenomenon the "Diderot effect."

This effect can operate in three distinct ways (McCracken, 1990):

- It prevents individuals from acquiring objects that might carry cultural significance incompatible with their possessions.

- When an "intruder" product is acquired, the Diderot effect forces the creation of an entirely new "Diderot unity" of harmonious products with this new product. The new disruptive acquisition that breaks a previous "Diderot unity" is called a "departure purchase."

- Finally, individuals can manipulate the effect to achieve specific symbolic goals. This effect occurs as individuals intentionally make purchases outside their existing unity as a means of personal experimentation, causing an expansion and reimagining of the self.

McCracken (1990) defines the “departure purchase” as any purchase with no precedent in the consumer's existing complement of products.

To identify the departure product, one only needs to determine that the consumer has departed from the usual consumption pattern, their existing “Diderot unity,” and consequently created a new one. McCracken also addresses factors that could prompt “departure purchases," such as product development - a new design, for example - or new personal life circumstances or events - such as marriage or a job change - or receiving a gift. Additionally, McCracken points out the lack of research into which products work better as departure products.

The literature hints at a broad distinction for categorizing the purchases that tend to follow a departure product into two primary types: proximal possessions and distal possessions. Proximal possessions share a direct functional or design relationship with the initial purchase, often aimed at enhancing utility, coherence, or aesthetic integration (Belk, 1988). Conversely, distal possessions lack a direct functional connection to the initial acquisition but serve to harmonize the broader material environment with the newly established aesthetic or symbolic standards set by the disruptive purchase (Belk, 1988). This typology helps understand the broader scope of the Diderot effect, emphasizing that it is not confined to immediately related items but extends to creating a cohesive lifestyle or environment around the initial purchase.

PREVIOUS STUDIES

Although the topic is succinctly mentioned in studies related to consumption (e.g., Zhong and Mitchell, 2010), as far as the authors know, only two studies focus directly on the "Diderot effect," hence the sparse literature review.

Davis and Gregory (2003) attempt to establish connections between creating new Diderot unities and "impulse purchases" as key departure products in a consumption context. In their qualitative study based on 19 in-depth interviews, the authors tentatively concluded that cognitive factors, such as the meaning attributed to products, aspirational lifestyles, and personal aspects, such as attending college or starting a new job, could be among the factors triggering "impulse purchases." These purchases can constitute "departure products" and thus contribute to creating new Diderot unities. Finally, they suggested conducting further quantitative research with a larger and more representative sample to validate these findings.

In another study where the Diderot effect is the central theme, Song *et al.* (2021) focus on the implications of the Diderot effect in the plastic surgery domain. The study is based on exploratory interviews with ten women and aims to understand how plastic surgery and the consequent changes to a consumer's self-image can alter consumption practices. The authors found that cosmetic surgery can lead to new consumption patterns based on the new self-image - meaning that consumers seek to eliminate self-discrepancies by consuming new products and services to match the newly enhanced physical self. Similar to previous research, the authors propose the possibility that personal factors, in this case, changes in the self, can spur new consumption patterns. Future research suggests exploring other contexts, such as how life events can change a person's self-concept and lead to new purchases in a negative spectrum and how changes like aging, accidents, and other adverse changes can alter consumption patterns. Despite the study's limitations, such as the sampling size, methodology, and replicability, the authors identified the manifestation of the Diderot effect.

The literature confirms that the Diderot effect is well-established (McCracken, 1990) and has a solid theoretical base. This study diverges from previous studies because it aims to understand how the Diderot effect might tangibly impact an individual's purchase behavior, specifically its economic consequences for consumers and its main features and, therefore, how merchants can use these findings. In addition, this research seeks to follow up on future research suggestions from these two studies by adopting a quantitative methodology based on a data-driven approach, allowing for the inclusion of larger and randomized samples.

Building upon the literature review and the identified limitations of previous studies, this study seeks to answer this central research question: "What are the tangible effects and repercussions of the Diderot effect on the purchasing behavior of consumers?". Several reasons prompt the exploration of this question. While Davis and Gregory (2003) and Song *et al.* (2021) shed light on factors influencing the creation of new Diderot unities, a gap remains regarding their formation process. This study employs a data-driven approach to fill this gap and delve deeper by addressing secondary questions that elucidate the impact of the Diderot effect on consumer purchasing behavior, namely, 1) how long does it take after a consumer's pattern is disrupted to acquire the following products that will be part of the new Diderot unity, 2) how many more complementary purchases consumers tend to make to fill in this new unity. In his study, McCracken (1990) defined how a "departure purchase" and the new Diderot unity can be identified. This research aims to follow up on this by trying to understand the qualitative impacts on the consumers' purchase patterns, specifically, 3) what the most common types of complementary products are part of that Diderot unity. Armed with this information, it will be possible to provide a tentative answer to a final secondary question: 4) what is the ultimate cost of all these products?

RESEARCH MODEL

The proposed research model aims to provide a structure based on the literature review to answer the research questions.

Due to the broadness of the topic and data availability, the study had to be restricted to a specific product and one marketplace. As transactional data from companies are complex to obtain (due to privacy and mismanagement concerns), this research aims to validate and evaluate the consequences of this effect by collecting data from online reviews. To do so, this study will determine if a particular product suitable for "departure purchase" could prompt a cascade of related purchases.

The literature review was a starting point for the model depicted in Figure 1, mainly on how the Diderot effect works and what might influence its manifestation. Based on McCracken's (1990) definition of the main features of a product that can work as a "departure purchase," the first hypothesis is:

H1 The selected product for the study has the potential to alter a consumer's typical purchasing behavior.

Secondly, it is hypothesized that the "departure purchase" is not an isolated event but is instead likely to catalyze the formation of a new Diderot unity:

H2 This "departure purchase" can lead to a spiral of new complementary products.

Thirdly, based on Davis and Gregory (2003) and the potential connection between "impulse purchases" and the formation of new Diderot unities, it is hypothesized that time may influence consumers in procuring new complementary products that are coherent with the "departure purchase":

H3 This purchase compels consumers to acquire new complementary products in a short period.

Finally, based on McCracken's (1990) assumption that consumers tend to look for coherence, it is hypothesized that the occurrence of at least one related purchase following the "departure purchase" results in the formation of a new Diderot Unity, thereby confirming the manifestation of the Diderot effect. Increased subsequent purchases would further solidify the Diderot Unity and amplify the manifestation of the Diderot effect.

H4 The new set of products generates a new Diderot unity.

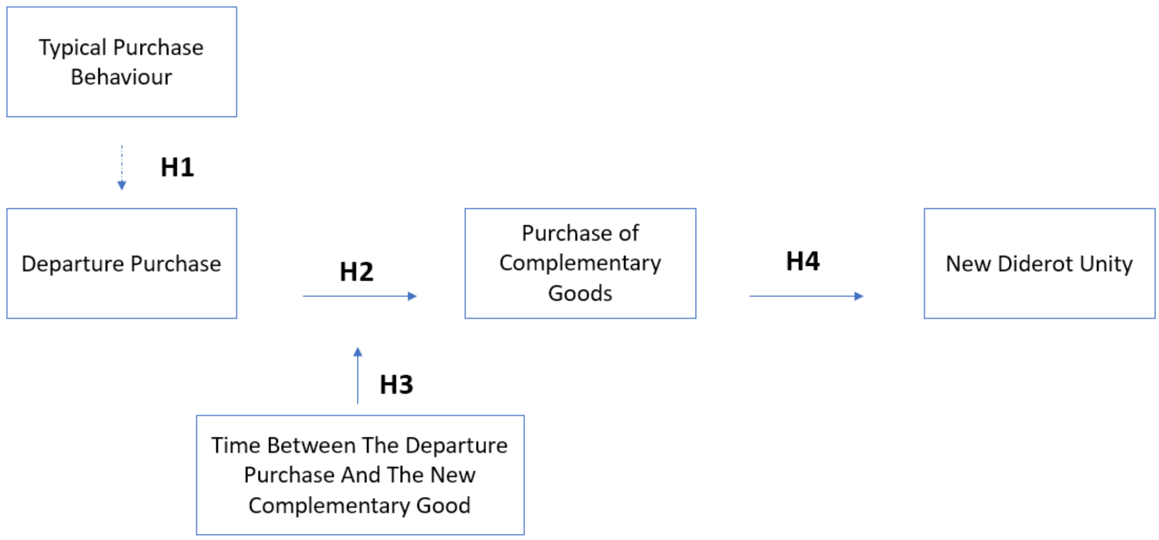

Figure 1 - Conceptual Model

METHODOLOGY

RESEARCH APPROACH

To fulfill the study's intent, this research used indirect data collected from an online retailer, further employed to perform descriptive research through a data-driven approach. As most companies consider their transaction data proprietary and understandably keep it confidential, obtaining a transactional database from the retailer was impossible. For this reason, this study’s database had to be built through web scraping of the information available on the website’s users’ review content. Web scraping is an automated method of gathering data from websites crawled by bots and organizing it logically. It is also known as web harvesting or web data extraction (Landers *et al.*, 2015). This process made it possible to draw a reliable inference, or proxy, of a customer’s sequential purchases made on the website. All the departure products’ reviews used in the study were “Verified Purchases,” which means that the user who wrote them very likely bought the product, according to the company’s verification. For all other purchases, to have a vast database, there is an assumption that each review corresponds to a purchase.

Based on these assumptions and data availability, a general approach to the study was developed to guide the research forward. As shown in **Figure 2**, this approach is composed of five steps.

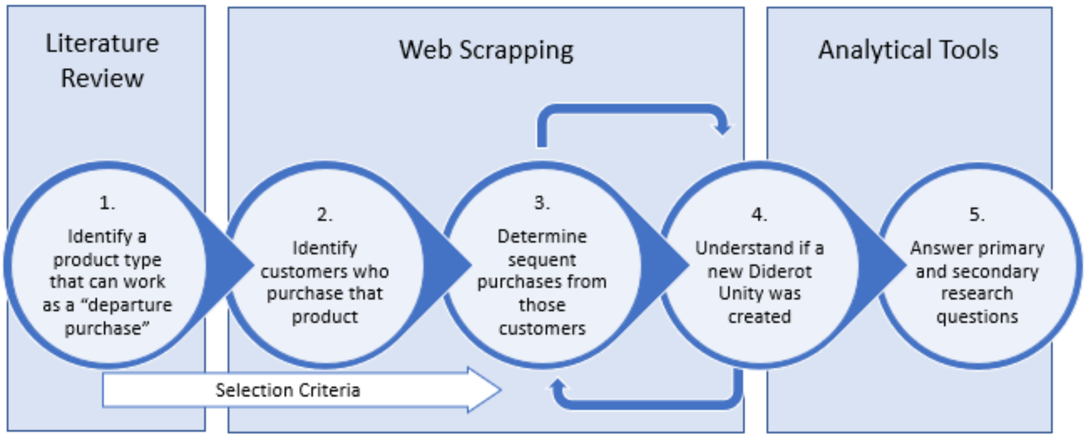

Figure 2 - Research Approach Diagram (self-elaboration)

The first step was identifying a suitable product type for analysis. For this, a concrete product type from a specific category was selected, and then, within that product type, the most popular products were chosen for analysis. Afterward, all these product reviews were collected through web scraping. The collected reviews allowed access to the user's profile, where gathering all the user's reviews was possible.

Data mining techniques attest to the relationship between the "departure purchase" and subsequent purchases. One is the Generalized Sequential Pattern algorithm (Srikant *et al.*,1992), a sequence mining algorithm that removes non-frequent items to find the most common transactions.

SELECTION CRITERIA AND SAMPLE

The U.S. version of Amazon (amazon.com) was chosen for the data collection because it is one of the world's biggest online marketplaces and the largest online retailer in the United States of America, capturing 49% of all electronic commerce in 2018 (He and Hollenbeck, 2020). The magnitude of Amazon allowed the collection of a robust number of observations. The platform is also comprehensive in terms of worldwide presence. It is also interesting to notice that the online context makes consumers more susceptible to irrational purchases (Chen and Zhang, 2015). Finally, it allows for rich, comprehensive, and reliable data collection since it is possible to identify, for instance, "Verified purchases," which confirms that a reviewer is genuinely the purchaser of the product.

Due to the topic's broadness and dimension of data analysis, there was a need to define a concrete product for assessment. It is hypothesized that a laptop could likely be a "departure purchase," meaning it is the kind of product prone to disrupt normal consumer behavior. There are two main reasons for these assumptions. First, due to the technological development cycles, purchasing a laptop is likely to generate a disruption from any previous acquisitions (Hoang *et al.*, 2009). According to McCracken's theory, product development is one of the aspects that could prompt departure purchases (McCracken, 1990). Secondly, owing to its substantial cost, a high-end laptop is often a non-complementary acquisition in many consumer scenarios. Like a luxurious robe, acquiring a high-end laptop can have symbolic significance, surpassing utilitarian purposes. It is well-established that material possessions serve as a medium for signaling status within society.

Additionally, empirical research indicates that laptops are commonly perceived as symbols of status and are linked with metrics of status signaling (Wang *et al.,* 2006). A high-end laptop may enhance lifestyle, reflecting the user's aspiration for cutting-edge technology and innovation. It is also a product that is prone to be bought online since, contrary to clothes or garments, there is no substantial benefit from trying it on physically before purchasing (Comegys *et al.*, 2009). Furthermore, acquiring a laptop, as it might be used in public, can be seen as a statement of identity and aspiration, echoing the Diderot effect's notion of acquiring items that elevate one's perceived status. Moreover, finally, unlike niche luxury items, laptops are a type of good with a broad appeal that anyone might typically acquire, regardless of age, sex, religion, geographical location, or even income level. This universality allows us to explore departure purchases in a context that may resonate with a broader audience.

As it was not possible to find a reliable source with data regarding the best-selling models of 2020 worldwide, the laptops under analysis were based on the best-selling models list from Amazon (https://www.amazon.com/Best-Sellers-Laptop-Computers/zgbs/electronics/565108), according to the data available on the website. The data that constitutes this list was gathered on September 30, 2021. From the products listed, this study selected the ones launched before September 30, 2020, – based on the information provided by the website's HTML field tag "Date First Available." This selection provides a minimum of one year for the user to make consequent purchases from the laptop launch date until the data gathering date.

Among laptops selected through the previous criteria, a selection of the best-selling model with over 800 product ratings was performed. This selection ensures the inclusion of the most popular laptops and makes it more representative of the average laptop purchaser.

This study only considered reviews from users based in the U.S. This sampling criterion was used since the U.S. version of Amazon.com only allows access to the review history of U.S.-based reviewers. This information is required to infer consequent purchases and thus build the transactional database. As the study aimed to create a transactional database that was as reliable and as close to reality as possible, only "Verified Purchases" laptop reviews were scraped. As noted before, this HTML tag can be gathered through the reviews' data.

Cut-off dates were also defined for the analysis so it would be possible to scrutinize the manifestation of the Diderot effect in a consistent timeframe. Consequently, as described in **Figure 3** only laptops with verified purchasers' reviews written until March 31, 2021, were selected for analysis.

One of this study's limitations is that the purchase date is unavailable. Thus, it was assumed that the review date coincides with the purchase date. By selecting March 31, 2021, as a cut-off day for the purchase date, it was possible to analyze at least six months of purchases between the possible latest launch date and the purchase date. These six months are assumed to be an acceptable interval for acquiring a recently launched laptop.

From the latest purchase date, March 31, 2021, consequent purchases were analyzed until September 30, 2021, allowing at least another six months to determine if the Diderot effect occurred in consequent purchases. It was also defined that the latest antecedent purchases occurred six months before the laptop's purchase date.

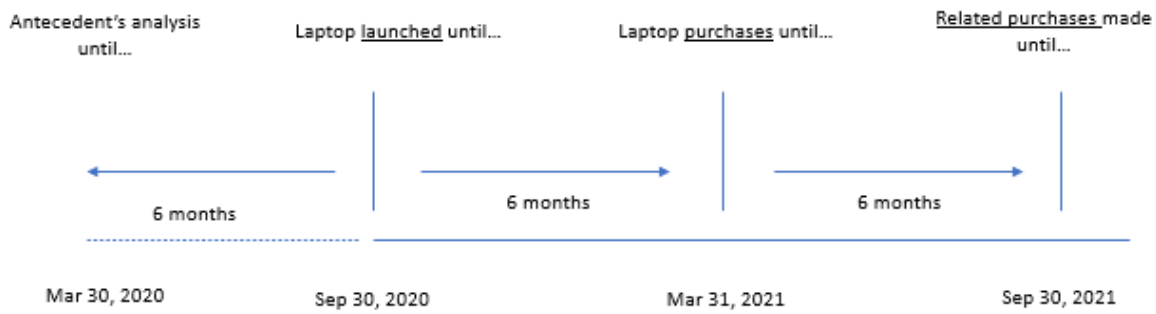

Figure 3 - Study's methodological timeframe

DATASET AND VARIABLES

Based on the selection criteria and the information available throughout the website, the tools and requirements were defined to approach the data collection and dataset construction.

A web scraping tool was built in Python. This tool was based on the Selenium WebDriver, a web framework that allows the execution of cross-browser tests and is used to automate web-based application testing to verify that it performs expectedly (Gojare *et al.*, 2015), and the Beautiful Soup library. This Python library uses an HTML/XML parser and turns the web page/HTML/XML into a tree of tags, elements, attributes, and values (Vallejo-Huanga *et al.*, 2019). Using Microsoft Azure Machine Learning Studio, the web scraping tool ran on Google Cloud Virtual Machines between September and December 2021 and in January 2022. Further, a detailed process was developed to guide data collection and database building. This process went as follows:

Step 1: Scrape the list of the best-selling laptops from Amazon, from which the chosen laptops fulfilled the criteria.

Step 2: The reviews from each laptop were scraped using the tool above, and all the reviews fulfilling the previously mentioned criteria were gathered.

Step 3: We accessed each profile of each user who reviewed the laptop, scraped each "Verified review," and collected it.

Step 4: All user reviews were collected and classified as "Antecedent" or "Subsequent " purchases related to the laptop acquisition.

Step 5: Finally, the product information for each product mentioned in the reviews was retrieved and accessed to gather data such as price and taxonomy—or product categorization.

The data available through the HTML tags on Amazon.com were used to select the most important attributes for further analysis. The days between purchases and the order in which they were made were also used to generate derived variables. Table 1 provides a complete description of these variables.

VARIABLE NAME	***DEFINITION***	***POSSIBLE VALUES***	***TYPE OF VARIABLE***
UserID	The user's name on the Amazon Website;	Names	Original
Product Name	The product definition as it appears on the Amazon;	Names	Original
Review Date	The data of the review, which we will infer as being the transaction/ purchase date;	Date	Original
User star rating	The rating, from zero to five, that the user attributed to the purchased product	0 - 5	Original
Average_star_rating	The average rating of the product, from zero to five	0 - 5	Original
Number of ratings	How many people rated the product	Number	Original
Verified_purchase	A verification feature that confirms if the person who reviewed the product had, in fact, purchased it	1 = Yes 0 = No	Original
Review-title	Title of the review	Text	Original
Reviewtext	The review content	Text	Original
Price	Price of the product	USD	Original
Product Category_x	How the product is categorized on the Amazon website, which can be as deep as 9 levels.	Name of the category	Original
Days between purchase & laptop	Number of days between the original laptop purchase and the purchase in question	Number	Derived
Ant_Cons_Orig	Determine if a specific item is a Consequent purchase toward the laptop purchase or an Antecedent purchase	Antecedent, Consequent, Laptop Purchase	Derived
Rank	A purchase order concerning the laptop purchase	Ordinal	Derived

Table 1 - Variables under analysis

Figure 4 offers an overview of the sample's main features—the collected data comprised reviews for 33 best-selling laptops on the U.S. Amazon website. A total of 169,568 transactions (reviews) were gathered from 11,933 unique users (before data pre-processing).

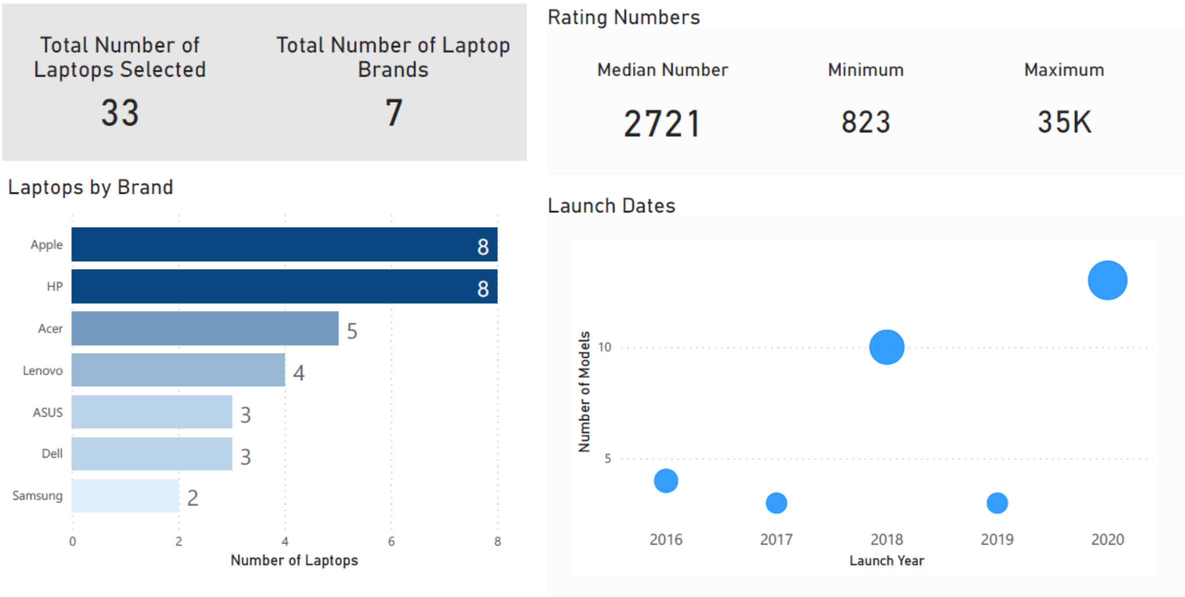

Figure 4 - Details of sampled computer models

The data was further pre-prepared and cleaned. Some specific data points were only partially available on the Amazon website. These cases were mainly the result of product discontinuation, lack of current product availability (vendor stock), or the website's design not allowing scraping of specific information (typical on specific Apple products).

Due to these limitations, some product categories were manually assigned based on keywords (for example, some computer mice were not sub-categorized by Amazon as "Laptop Accessory" but categorized as "Computer Mouse"). Hence, the researchers manually performed this categorization process. Products without available information (products that were available in the past but not at the moment of data collection) were removed, and invalid product links (primarily from discontinued products that the vendors no longer sell) were also excluded.

Before this diligence, all observations lacking information were re-scraped, targeting different HTML tags available to gather data to help inform categorization and price. This allowed this study to keep the data as close to reality as possible. Despite these efforts, 50,986 rows had to be removed from the original dataset due to missing data, unreliability, or failure to meet the criteria, leaving the final dataset with 118,582.

DATA ANALYSIS

The Generalized Sequential Pattern algorithm was used to validate whether the Diderot effect was present. It is assumed that if a substantial quantity of complementary products was purchased following the laptop purchase, this would indicate the presence of the Diderot effect.

The Generalized Sequential Pattern (GSP), an algorithm that helps find sequential patterns in sequential databases, was proposed by Srikant *et al.* (1992). It uses an approach similar to the *Apriori* algorithm for discovering sequential patterns. The input data for this algorithm is a data sequence, which is a list of transactions where each transaction is a set of items (Ramakrishnan and Agrawal, 1996). In this study, the list of transactions represents the purchase history of an Amazon user. This algorithm aims to find all sequential patterns with user-specified minimum support, defined as the minimum percentage of data sequences that include the pattern.

This study also aims to answer secondary questions related to the consequences of the Diderot effect, namely the costs and the number of consequent purchases it generates. It also gathers insights into the time it might take to manifest. Statistics and visualizations were also used to tackle these secondary questions.

RESULTS

Before further research on the relationship between laptop purchases and consequent purchases, an exploratory data analysis was conducted to help understand the data and its major features. After treatment (removing duplicate and unreliable data points), the final dataset contained 118,582 observations, or product purchases, from 11,678 unique users.

Number of Purchases and Frequency

Customers made between 1 and 1,099 purchases, including the laptop, with most users purchasing between 1 and 20 products. The median number of purchases was five, and the average was 12. Figure 5 a) depicts the purchase distribution and shows that 2,811 users only purchased the laptop without making any consequent purchases. In fact, 60% of users made five purchases or fewer.

Frequency tells us how often the customer purchases. In this case, it is represented by purchasing one or more products on the same date, referred to as a “transaction.” As Figure 5 b) shows, most customers only made one transaction. The total number of transactions recorded was 60,487, with 3,665 users only making one transaction. The median number of transactions was 3, the average 5, while the maximum number of transactions was 167. Similar to the purchase analysis, it is possible to infer that one-third of this database’s users had a low frequency of purchases on Amazon – they were not regular customers - which makes the ones who bought laptop-related products even more noteworthy. The average number of products purchased per transaction was 2.

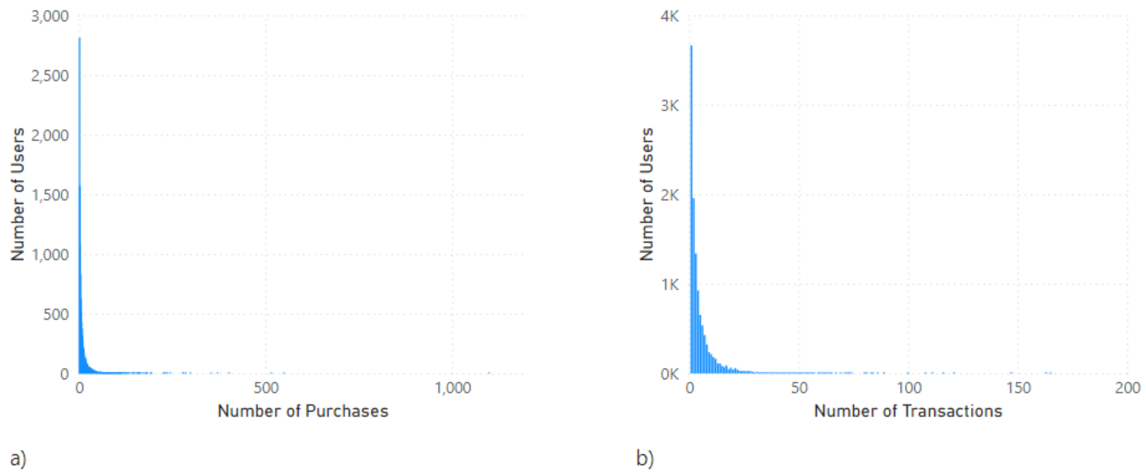

Figure 5 – a) Overall distribution of purchases b) Overall distribution of transactions (frequency)

Days between purchases and frequency of purchases after the laptop purchase

The following plots show how long, after the laptop purchase, other purchases tend to be made, measured as the median number of days, including items beyond computer accessories. The first consequent purchase tends to be made quickly, within the first ten days. The subsequent ten purchases are completed within 200 days of the laptop purchase. The maximum number of purchases by a customer was 1,098, excluding the purchase of the laptop itself; the median number was 12, and the average was 32. Figure 6 a) shows that the median time between purchases tends to decrease around the 500th purchase. It is possible to deduce that it happens because only extreme users are accounted for when the number of purchases increases. Those users tend to have a small number of days between every purchase – indicating a high purchase frequency. The median was used because of the high variance of the data – for instance, the minimum number of days for the first consequent purchase for some users was 0 days, while the maximum number of days for other users was 1,448 days.

Figure 6 b) shows the frequency of transactions – an aggregation of the purchases made on the same date. The first transaction following the laptop purchase occurs within 82 days. The second to fifth transactions tend to be made within the first 200 days after the laptop purchase.

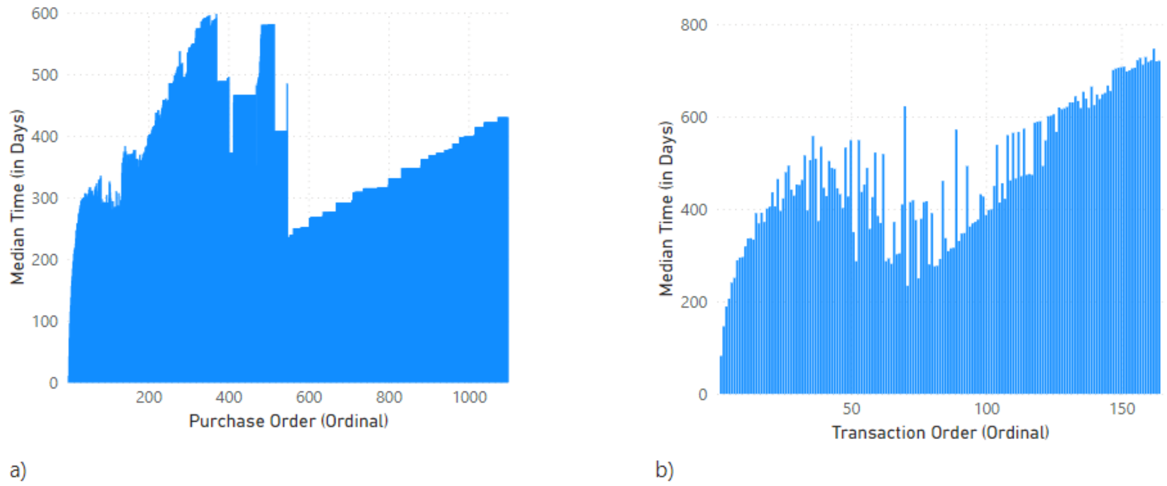

Figure 6 – a) Overall distribution of median days between purchases and the laptop purchase day b) median days between transactions and the laptop purchase date

Most purchased products

The analysis was performed considering four different levels of product taxonomy. Specifically, product categorization, ranging from the broader scope of Product Category Granularity 1 - for instance, "Electronics" - until the more specific Product Category Granularity 4 – which would be a specific product such as a "Webcam." Since laptops are within "Electronics" but are the product under analysis, they were categorized under "Laptops." This category was created to simplify the analysis.

Figure 7 a) shows that granularity level 1 categories are too broad to offer meaningful insights. Figure 7 b) reveals that at Granularity Level 2, 'Laptops' and 'Computer & Accessories' emerge as the most purchased categories, suggesting the Diderot effect may be present. Diving deeper into purchased products' specificity, it is possible to see in Figures 7 c) and d) that the number of purchases for each sub-category started to decrease, which is natural since the granularity increased. However, in Figure 7 d), some of the most purchased products were cases, earbuds, keyboards, and mice, which can be directly related to the original laptop purchase.

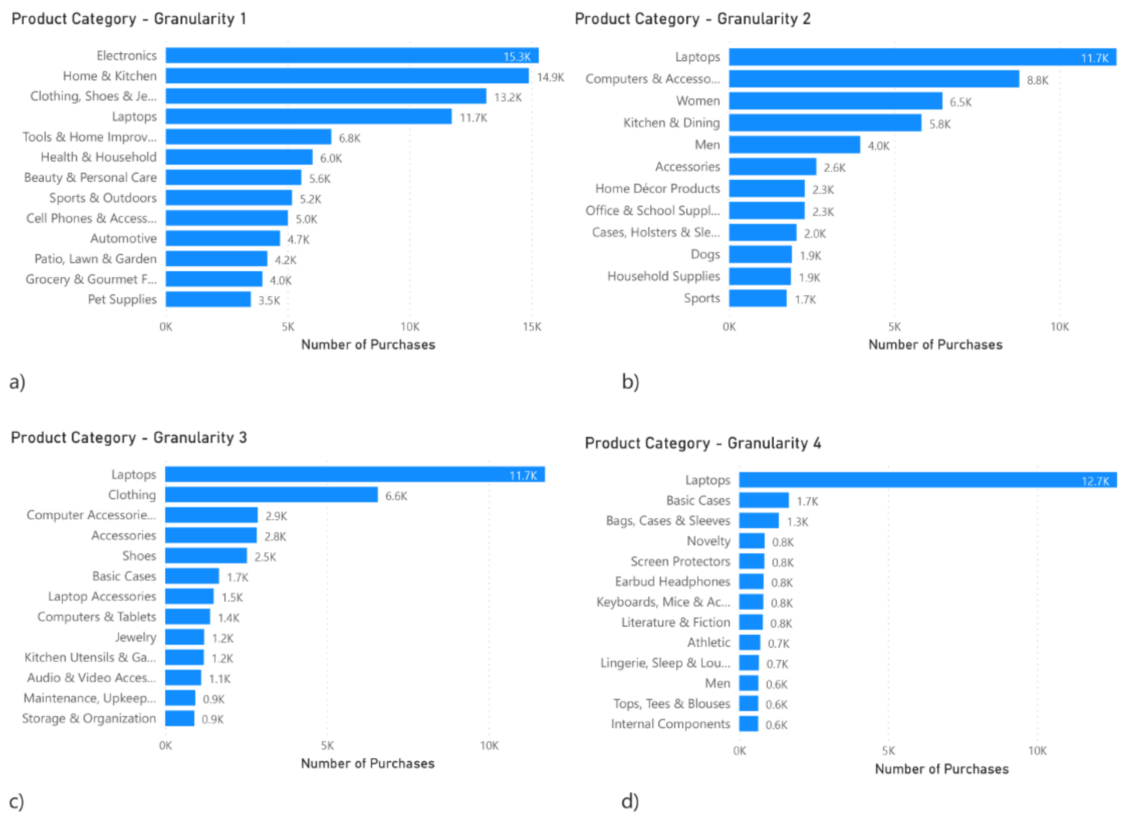

Figure 7 - Products with the highest number of purchases on the dataset. a) Lowest level of granularity. b) Second lowest level of granularity. c) Third level of granularity d) Level with the highest granularity.

Purchase sequence analysis

All the data was analyzed using the GSP algorithm at the four levels of taxonomy – or product categorization - with a minimum support of 0.5%, corresponding to roughly 60 sequences containing the pattern.

After removing all “Antecedent” purchases, 11,678 sequences were left for analysis. Each sequence lists all the purchases made by a specific customer.

Looking at the results for the broader level, Level 1 (Table 2), one can identify that the most common patterns are related to laptops, followed by other electronic devices. People who make more than one purchase tend to buy another electronic item. This finding is substantial when most users only made one purchase. The most common sequence with three elements is (“Laptop,” “Electronics,” and “Electronics”), which occurs in 394 transactions, or 3.37%. The most common pattern with four elements is (“Laptop,” ”Electronics,” “Electronics,” “Electronics”) – it occurs in 136 transactions or 1.16% - which reinforces the idea that after purchasing a laptop, consumers buy other electronic products.

SEQUENCE	SUPPORT	SUPPORT (IN %)
('Laptop', 'Electronics')	1679	14.38%
('Laptop', 'Home & Kitchen')	1098	9.40%
('Laptop', 'Clothing, Shoes & Jewelry')	1071	9.17%
('Laptop', 'Cell Phones & Accessories')	489	4.19%
('Laptop', 'Tools & Home Improvement')	450	3.85%
('Laptop', 'Health & Household')	408	3.49%
('Laptop', 'Electronics', 'Electronics')	394	3.37%
('Laptop', 'Electronics', 'Electronics', 'Electronics')	136	1.16%

Table 2 - Most common sequences for laptops on level 1 of granularity, output GSP algorithm

At the second level of specificity, the most common sequence is “Laptop,” followed by “Computers & Accessories.” The most frequent sequence with three elements is the initial “Laptop,” followed by two purchases of computer accessories. This pattern indicates that a laptop purchase might lead to purchasing accessories. Again, considering that approximately one-third of all users under analysis (2,811 users) only made one purchase, it is remarkable that from the 8,867 users who purchased more than one product, 1,033 purchased a Computer Accessory – which represents almost 12%.

At the third level of specificity, the granularity increases, reducing the support for the most common sequences while increasing the level of detail. At this level, the most popular sequences are related to laptop accessories (cases, earbuds, and components). The support for these sequences is 1,533, or 13%. Notably, 203 people bought a laptop after the original purchase, suggesting that the initial purchase did not act as a “departure purchase” for these users.

At level 4, the sequences with more than one element with higher support are also related to laptops. For this level of categorization, the GSP algorithm was also used to explore even lower levels of support – going as far as finding sequences with minimum support of 0.09% - 10 transactions within the entire dataset. As shown in Table 3, it is possible to see that the most common complementary products are “Bags, Cases & Sleeves,” “Basic Cases,” “Keyboards, Mice & Accessories,” “Earbud Headphones,” and “Laptop.” It is also interesting to notice that the most common sequence is “Laptops” and “Bags, Cases & Sleeves,” products made to protect this device, which suggests laptops are, in fact, products of meaningful importance for most users.

SEQUENCE	SUPPORT	SUPPORT (IN %)
('Laptop', 'Bags, Cases & Sleeves')	224	1.92%
('Laptop', 'Laptop')	203	1.74%
('Laptop', 'Basic Cases')	159	1.36%
('Laptop', 'Keyboards, Mice & Accessories')	105	0.90%
('Laptop', 'Earbud Headphones')	103	0.88%

Table 3 - Most common sequences for laptops on level 4 of granularity, output GSP algorithm

Purchase of Computer Accessories

The purchases of laptop accessories were also investigated to study the Diderot effect, specifically an overview of products classified as "Computer & Accessories" at level two of granularity. A total of 7,828 accessories were purchased (excluding other "laptops" purchased after the original laptop purchase) by 3,335 unique users. As Figure 8 shows, most of these users bought just one accessory. The maximum number of accessories purchased by a single user was 52, clearly an outlier in this dataset. The average number of accessories purchased by each user was 2, and the median was 1. Interestingly, a noteworthy number of users, even if not in a direct sequence of purchasing the laptop, end up buying a laptop accessory. This fact is already a validation of the Diderot effect.

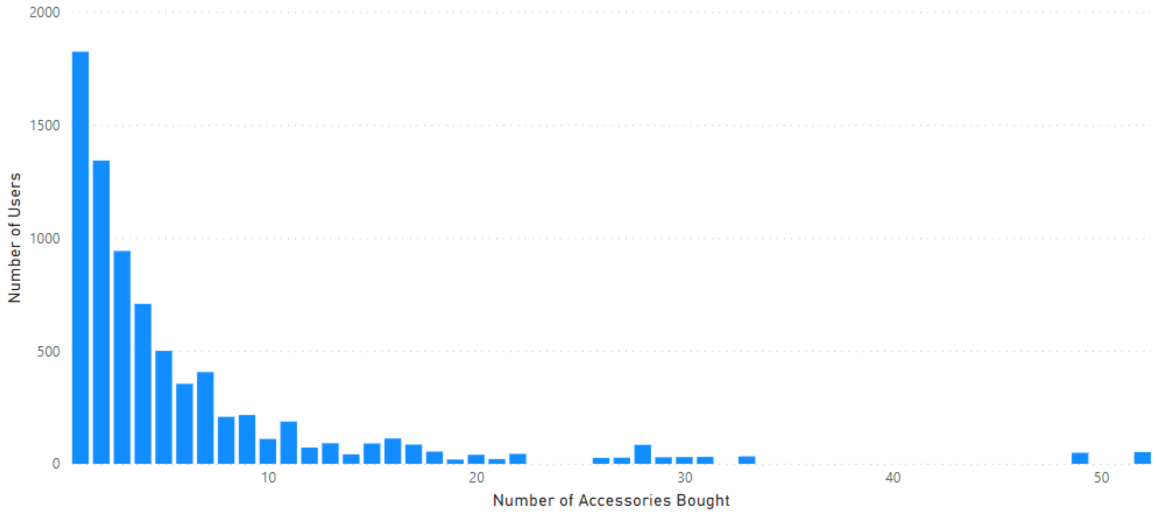

Figure 8 - Distribution of accessories bought per user

Figure 9 a) shows that most accessory purchases tend to be made simultaneously or in a purchase order right after acquiring the laptop. Around 85% (2,854) of users who purchased accessories bought their accessories within the first ten purchases following the acquisition of the laptop. Those ten purchases correspond to around 60% of all laptop accessories bought.

Regarding the timeframe, as illustrated in Figure 9 b), most computer accessory purchases tend to be made within the same transaction as the laptop, hence the zero days of difference between purchases. Nevertheless, these numbers should be interpreted cautiously since the underlying date is sometimes a proxy for the actual purchase date.

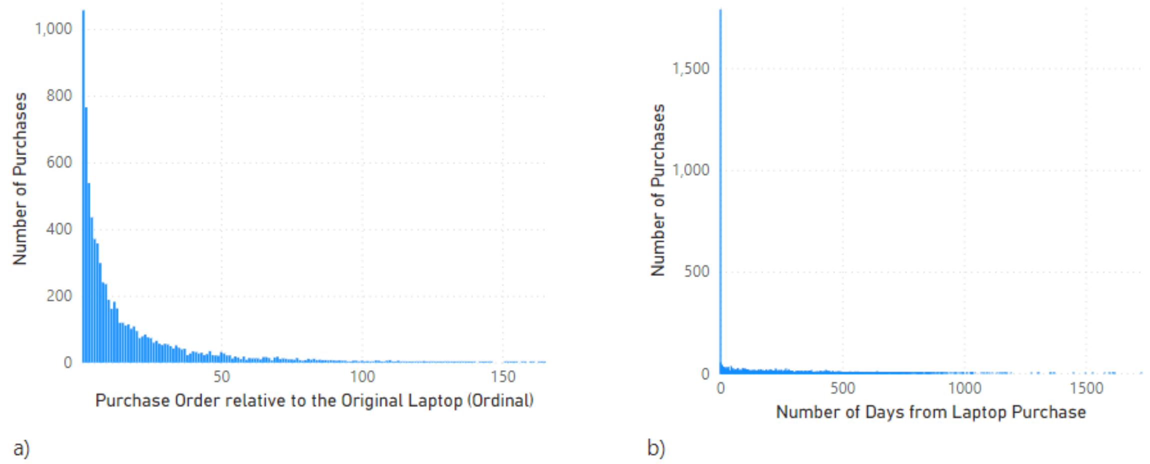

Figure 9– a) Plot of overall distribution showing which purchase order people tend to buy a "Computer Accessory." b) Plot the overall distribution of days after the original laptop purchase. People tend to buy a laptop accessory.

Finally, the study inferred the potential financial impact of the purchase of complementary products, thus the monetary tangibility of the Diderot effect. Figure 10 shows the money spent by users who purchased laptop accessories. It is relevant to notice that over 30% of values are missing from the dataset for the variable "Price." To address these missing values, the price of those products was defined as zero. According to the data, 540 users did not spend any money on accessories – which refers to the missing values for the price variable – while the maximum amount spent by a user was 3,368 USD. The average amount spent was 86 USD, and the median was 26 USD. It is highly plausible that the financial impact is even more significant, as those 540 accessories with a price of zero likely had a cost at the time. The value of zero

USD when the data was gathered derives from a lack of information on the products' pages due to discontinuity or lack of stock. Again, these numbers should be considered cautiously due to the study's exploratory nature.

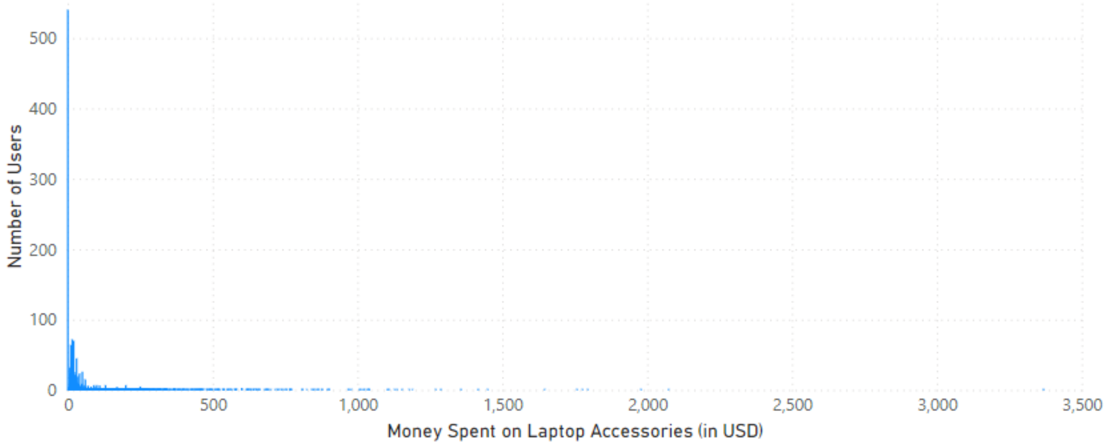

Figure 40 - Customers spending on "Computer & Accessories," from the users who bought a laptop accessory

These results show that if the support of most common sequences of laptops and related products are added up, over 10% of the people who purchase a laptop through Amazon.com tend to purchase laptop accessories, namely protection cases, headphones, keyboards, mice, or monitors, amongst others, right after the purchase of the laptop or on the same transaction. This fact might be explained by bundling or cross-selling promotions happening at that time, or perhaps it can be hypothesized that a customer might be more predisposed to buy more products if their mind is already predisposed to make a purchase – namely, the original laptop. This number is even higher if we account for all unique users who purchased a product from the "Computer & Accessories" category – 3,335, around 29% of the total 11,678 users in the study's database. These are noteworthy facts if it is considered that 2,811 users, around 24%, present in the sample only made one purchase. This number can be even more substantial if it is considered that only around 1.5 percent of customers provide a review for products bought online (Anderson and Simester, 2014). While these products may depend on the existence of a primary product, they often serve an interconnected purpose. For instance, a laptop case is more than a protective accessory; it also adds to its portability, making it easier for the user to carry.

Moreover, it helps maintain its display quality. Screen protectors, headphones, keyboards, and internal components similarly enhance the user experience and functionality of the primary product. The purchase of these items might be part of a user's desire to upgrade or personalize their technology setup. Upgrading internal components, getting a new keyboard, or buying high-quality headphones can be seen as attempts to create a more sophisticated and tailored user experience. While these products may be more interdependent, the nature of modern technology usage and consumer preferences might still align with the essence of the Diderot effect. Hence, according to the visualization and the most common sequence patterns, purchasing a laptop computer can prompt further related purchases and, consequently, manifest the Diderot effect.

DISCUSSION AND CONCLUSIONS

RESEARCH CONTRIBUTIONS

In terms of contributions to the academic world, despite its tentative nature, this study's novel approach and methodology provide a benchmark for further data-driven research based on readily available indirect data, namely, online reviews. This method might inspire other researchers to use online reviews as a proxy for transaction data and help democratize data-driven research by enabling more organizations to conduct behavioral analyses without relying on proprietary datasets. Additionally, by relying on publicly accessible data, this study highlights an ethical and transparent approach to consumer data analysis. This can serve as a model for conducting business analytics research while respecting consumer privacy and data protection regulations.

The study bridges the gap between theoretical consumer behavior and practical business analytics, inspiring future models that anticipate rational buying patterns and tendencies that drive purchasing decisions. Combining behavioral biases like the Diderot effect with transaction data and machine learning allows for more sophisticated predictive models that account for consumers' irrational tendencies, leading to more accurate forecasts and strategies. The same framework can be extended to identify other systematic biases within transactional datasets, helping practitioners detect irrational behaviors in their studies.

Indeed, data has been an issue in behavioral economics due to the lack of replicability in certain studies (Schimmack, 2017). This study sheds light on the possibility of applying a data-driven approach using open-sourced data, which could enhance the replicability of such studies while offering larger and broader samples.

Another contribution of this study lies in its pioneering nature, as it establishes a reference point for how the Diderot effect manifests itself. If McCracken (1990) introduced the basic notions of how this effect operates, this research could extend them by laying the early foundations on how it manifests itself in consumers' lives. Some key facts that can be concluded from the data are that the Diderot effect seems to start manifesting concurrently as the "departure purchase." From then on, the most substantial number of subsequent purchases tend to be made simultaneously or within ten purchases from the "departure purchase." The most frequently purchased products are directly related to the expected purchase.

In their studies, Davis and Gregory (2003) and Song *et al.* (2021) focus on the factors that could be triggering "departure purchases" resulting in new Diderot unities. By approaching the problem from the purchased product and not the reasons behind the purchase, this research expands on previous works providing insights into the determinants of forming new Diderot unities. This newly gathered knowledge allows further exploration of the subject of those studies by, for instance, offering a benchmark to study which products are more likely to become departure products after specific lifecycles.

MANAGERIAL IMPLICATIONS

The results of this study show this phenomenon's relevance and validate the theory (McCracken,1990). Retailers could better understand this effect on their transactions using their transactional database. It could have an essential impact on fulfilling customer´s needs. Identifying these sequences could help build more accurate recommendation systems and product search engines. It can also guide the conception and marketing of product bundling, cross-selling, up-selling, pricing policies, or advertising campaigns. In a more indirect approach, companies could use the results of these studies to extend product portfolios into newer categories or manage their product stocks according to predicted market needs.

From a practical standpoint, this approach can also contribute to a more refined market segmentation by identifying consumer segments more susceptible to the Diderot effect. For example, analytics teams can profile consumers who tend to make complementary purchases after a significant acquisition, allowing for more personalized marketing and product recommendations tailored to their purchasing behavior.

This study suggests the potential for extending product portfolios into newer categories based on consumer needs. Companies can use this insight to explore new product categories that align with customer behaviors and preferences or optimize inventory based on predicted market needs, leading to more efficient stock management.

Another aspect that this study highlights is the importance of the timeframe in which the related purchases are made. Most accessories were bought at the same time as the laptop, but there was also the fact that many users on the dataset only made one purchase. This pattern shows that consumers seem more likely to spend even more on unforeseen purchases when they are already spending on an expected purchase. Thus, we can infer that it is easy for consumers to spend “more” money if they are already prepared to spend “some” money. To take advantage of such conclusions, companies, and retailers, in general, can use this insight to develop models that account for the timing of purchases, optimizing marketing campaigns and recommendation engines to align with consumers' predisposition to spend, which might place increasing worth on their interactions with consumers by, as an example, proposing much more relevant complementary products and services during the expected purchase – if that purchase can be considered a potential “departure purchase”.

While this study focuses on laptops and complementary purchases, the methodology can be generalized across different industries (from fashion to home goods). Organizations can apply similar approaches to identify and exploit the Diderot effect in their specific sectors, enhancing industry-specific marketing strategies.

LIMITATIONS OF THE RESEARCH

This study aims to validate the Diderot effect using primary data from an indirect source. It generates a series of assumptions and limitations.

One necessary assumption is that customers purchase all their products through Amazon. This study cannot account for the possibility that a customer might buy a complementary product from another retailer.

Assuming this, it is also necessary to believe that consumers review all their products and that all the products they reviewed constitute purchases—although this last one can be guaranteed through the "Verified Purchase" tick. Another assumption derived from this is that the review date is the same as the purchase date.

This study relies on the information on the website "at the moment" of the web scraping. Therefore, the product information, price, and categorization used in the study are based on the date when the data was collected, not the moment of purchase or review. Consequently, there is no information for some products, as they are no longer available on the website.

Regarding the Diderot effect specifically, it is crucial to know the current Diderot unity, which refers to the products a consumer owns. As that is almost impossible with this particular data-driven study, we can only infer that a Diderot unity is created by excluding users who had previously purchased a laptop through Amazon.

RECOMMENDATIONS FOR FUTURE RESEARCH

Much can be done to comprehend this effect and validate other cognitive biases primarily based on theoretical grounds, thus making behavioral science more data-driven, sound, valid, and applicable to organizations.

The findings of this study indicate that some directional pointers could be further explored. Future studies could conduct similar research based on a real transactional dataset, helping to confirm the findings of this research.

In his theory, McCracken (1990) mentions the need for more research to understand which products work better as departure products. This study aimed to tackle this gap to some extent, but its data availability limited it. Further data-driven research could expand this knowledge. One approach would involve taking a retail historical transactional dataset from a worldwide retailer and, without a specific product type or product in mind, analyzing the transactions per client and determining which are the most common Diderot unities generated by the products present in those transactions. From this analysis, it would be possible to hypothesize which products will most likely result in departure purchases within a wide range of product categories and their standard features. Such a study would also help to determine which product categories are more susceptible to the Diderot effect, leading to a whole new range of studies that could complement McCracken's theory.

The authors have no conflicts of interest to declare relevant to this article's content.

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