Customer Lifetime Value in E-Commerce: Assessing the Impact of Influencer Marketing

Masters's Thesis

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Abstract

Many articles have revealed the growing importance of social media and influencer marketing for companies. However, the optimal allocation of marketing resources remains a challenge, especially for the identification of influencers who can effectively target specific customer segments and, consequently, drive revenue for a company. This study intends to fill this research gap by providing a comprehensive overview of the role of influencer marketing on purchasing behaviors and Customer Lifetime Value (CLV). With secondary sales data of one of Europe's leading Direct-to-Consumer (DTC) fashion firms, involving a total of 1,830,739 purchases, this study specifically analyses customers' purchase patterns. Additionally, it examines the effects of different influencer categories within these patterns on revenue generation. The analyses distinctively investigate the impact of influencer-acquired customers compared to those acquired through organic purchases. This thesis then concludes with interesting implications regarding the selection of influencers for driving customer value. Lastly, it outlines limitations and promising areas of future research.

Keywords: *Online Influencer Marketing, Customer Lifetime Value, Purchase Patterns, Customer Journey, E-Commerce*

1. Introduction

With the emergence of Web 3.0 and the increasing relevance of being interconnected through the Internet, social media platforms have become prevalent in our everyday life (Leung, Gu, and Palmatier 2022, p. 227). Not only does this considerably impact how people communicate with one another, but also how companies approach their marketing activities. In response to these changes, companies increasingly turned to influencer marketing as a key approach for promoting their products and services. This shift in marketing is demonstrated by a tremendous growth of the global influencer market size. In 2023 the influencer market size exceeds $21b, representing more than a threefold increase since 2019 (Statista 2024).

The continuously growing influencer market not only highlights its increasing significance but also uncovers compelling areas for investigation. This thesis intends to provide a comprehensive overview of the role of influencer marketing in creating customer value and its effectiveness in driving sales and revenue. Given the diverse nature of influencers, this paper further investigates potentially varying effects across different types of influencers, categorizing them based on their follower count.

The first part of this thesis elaborates on the theoretical foundation of influencer marketing and how influencer marketing shapes the customer journey. This paper then introduces the concept of Customer Lifetime Value (CLV) as an important outcome metric for marketers to analyze a customer's future revenue streams. The main part of this thesis will then empirically examine the effects of influencer marketing on customer spending behaviors. With secondary sales data of one of Europe's leading Direct-to-Consumer (DTC) fashion firms, this paper analyzes customers based on their purchase patterns and whether their purchases involved an influencer or not. The, for our analyses used, dataset comprises a total 1,830,739 purchases. As the goal of this paper is to provide marketers with meaningful insights over specific customer groups, this paper particularly focuses on analyzing distinct customer segments exhibiting similar purchasing behaviors. To gain substantial insights, the analysis engages in detailed examinations of the most frequently observed purchasing behaviors. Of particular interest is the comparison of customers who are acquired through influencers to those that were not. In addition to the analyses on first purchases, this paper also investigates the repurchasing behavior of customers by analyzing metrics such as the interpurchase time.

Following the initial investigation, this paper subsequently examines the effects of influencer marketing on the purchasing behavior of high value customers, who contribute significantly more to a company's revenue compared to others. The analysis involves those customers accounting for the top 20% of the company's revenue. This distinction is of particular interest for marketers as it seeks to determine whether there are differential effects for high value customers or if the previous findings can be generalized across all customer segments.

The last chapter provides a critical assessment of both the findings and the data analyzed. It is followed by some managerial implications, outlines limitations and suggests promising areas of future research.

2. Theoretical Foundation

This chapter examines the theoretical background for the following analysis. The first part defines Influencer Marketing. The second part illustrates how Influencer Marketing shapes and has shaped the Customer Journey. The last part introduces Customer Lifetime Value (CLV) and elaborates on the importance of it for companies.

2.1 Influencer Marketing

Social media platforms like Facebook or Instagram are means of connecting people with each other through the Internet and entail the characteristics of building an online following quite easily (Leung, Gu, and Palmatier 2022, p. 227). The introduction of mobile devices further accelerated the use and population of social media platforms. Taking Instagram as an example, the dimension of social media use becomes apparent. In 2021 there were approximately 1.21 billion monthly active users on Instagram. These numbers are estimated to grow to 1.44 billion monthly active users by 2025, which then represents about 31% of the global Internet users (Statista 2023). It is thus not surprising that social media has become a fundamental instrument for marketing and communication efforts among corporations, organizations, and institutions. (Appel et al. 2020, p. 79).

Appel et al. (2020, pp. 81-82) predicted that a future development for social media comprises the rise of online influencers. Online influencers can be defined as individuals that were able to create a followership on social media while simultaneously serving as a role model or opinion leader for their followers (Leung, Gu, and Palmatier 2022, p. 228). Some influencers even achieve celebrity status, having accumulated an extensive base of followers (Leung, Gu, and Palmatier 2022, p. 228).

These trends caused the emergence of a new marketing strategy called Online Influencer Marketing (OIM). OIM is a marketing strategy, in which a company incentivizes online influencers to engage their followers in promoting a company's offerings (Leung, Gu, and Palmatier 2022, p. 226). Companies realized the potential of using online influencers for marketing activities and thus increasingly engaged influencers who then in turn promote the company's products. The dimension of the influencer market becomes evident when one considers that its value exceeded 21b $ in 2023 (Statista 2024). Leung, Gu, and Palmatier (2022, p. 227) in their paper differentiate OIM from other marketing strategies, such as celebrity endorsement or viral marketing, by three necessary features of OIM. Firstly, companies identify and incentivize online influencers; secondly, these influencers actively involve their audience in endeavours with commercial intent; and thirdly, businesses capitalize on the influencers' exclusive assets and capabilities to advertise their products or services. The authors compare OIM to the crowdsourcing of an influencer's resources (Leung, Gu, and Palmatier 2022, p. 248).

As previously mentioned, it is a well-known and effective marketing strategy to leverage celebrities or opinion leaders in business markets to enhance the promotion of a company's offering (Appel et al. 2020, p. 81; Knoll and Matthes 2017, p. 27). However, celebrity endorsements are often a very expensive marketing measure to implement and due to high costs not easily accessible for every firm, especially smaller ones. That is, why OIM has particularly caught traction for smaller brands as it represents a more affordable way of marketing, especially when using influencers with smaller follow count (Appel et al. 2020, p. 82; Leung, Gu, and Palmatier 2022, pp. 227–28). If online influencers are chosen for marketing efforts, they are generally expected to create content that fosters engagement among their followers (Wies, Bleier, and Edeling 2023, p. 383). An additional benefit for companies employing influencer marketing is the flexibility to promote their offerings either by influencer-created or other-created content (Leung et al. 2022, p. 111). Thus, companies can choose whether to use content created by influencers, by others, or a blend of both to align with their marketing strategies. Not only content-wise can companies benefit from influencers, but also from leveraging an influencer's assets such as follower-base, personal positioning, and follower trust (Leung, Gu, and Palmatier 2022, pp. 226, 248). Choosing influencers that have specific follower characteristics, offers the opportunity to target very distinct customer segments that can translate into a higher marketing effectiveness for the company (Leung, Gu, and Palmatier 2022, p. 248). Furthermore, a company can leverage an influencer's follower trust, as they are often perceived as genuine and maintain a communal bond with their followers (Leung, Gu, and Palmatier 2022, p. 238). Leung et al. (2022, pp. 93, 111) in their paper have additionally discovered interesting insights regarding marketing effectiveness. They claim that both follower size and influencer's originality positively affect marketing effectiveness. This means that influencers who communicate content or messages that are regarded as unique, or novel are generally more effective as they increase engagement elasticity among the followers (Leung et al. 2022, p. 111). Leung, Gu, and Palmatier (2022, p. 26) add to this that OIM proves to be a very effective marketing strategy for companies if influencers are perceived as authentic and reflecting their own influencer's styles. They claim that influencers achieve this by integrating marketing messages into the stories being presented to their followers.

It can be concluded that the development of the online influencer market represents a huge future market potential, especially in terms of reach. Appel et al. (2020, p. 83) claim that companies have realized the importance and effectiveness of OIM and are thus planning to further increase their marketing efforts in this domain. They further illustrate that several executives of global leading brands claim that marketing spendings in the realm of influencer marketing is due to increase.

2.2 Shaping the Customer Journey Through Influencer Marketing

In the previous chapter, it became clear that influencer marketing is a growing market with a lot of potential. In this chapter it is discussed how and in which way influencer marketing affects the customer journey and how companies can capitalize on that.

Customer journey theories have their roots in the 1960s, focusing on customers' decision processes, especially in terms of buying processes moving from need recognition to purchase and evaluation (Lemon and Verhoef 2016, p. 71). Following the definition of Lemon and Verhoef (2016, p. 76), a customer journey is considered to be a purchase cycle with multiple and dynamic touchpoints. They claim that there are three purchase phases within a customer journey. Firstly, the prepurchase phase, which incorporates aspects of customer interaction before the actual purchase. Behaviors such as need recognition, search and consideration are part of the prepurchase phase. Secondly, the purchase phase, which incorporates all aspects during the actual purchase of the customer. Behaviors such as choice, ordering and payment are part of the second phase. Thirdly, the post purchase phase, which then considers aspects that follow the actual purchase of the customer. Behaviors such as usage, consumption or post purchase engagement are part of the last phase. Looking at this definition, it becomes clear that there are multiple touch points between a customer and a firm along the customer journey. It is thus of great interest for marketers to influence the customer along this journey in a for the firm favorable way (Hamilton et al. 2021, p. 87).

As depicted in the previous chapter, the prevalence of social media and smart phones has a tremendous impact on our everyday life and thus on the customer journey. Smart phones have changed many of our daily routines, such as reading text messages, daily news or checking social media, even before we are leaving our bed in the morning (Grewal et al. 2020, p. 5). Over the course of the day, people constantly interact with social media or other applications and also engage in transactions like ordering food (Grewal et al. 2018, pp. 102–3, 2020, p. 5). There is, however, an even more important characteristic of social media to take note of. That is, that a lot of people have begun to use social media as their primary source of gathering information. And by the nature of social media, getting information is not limited to family or friends anymore, but to everyone on social media (Chen 2017, p. 613; Hamilton et al. 2021, p. 78). It is because of these characteristics that online influencers can have an influence on the customers journey and therefore provide value for a company. Online influencers have the potential to shape their follower's perspectives and behaviors through their actions, portrayals, and depictions on social media. (Leung, Gu, and Palmatier 2022, p. 228). Appel et al. (2020, p. 82) in their paper illustrate how online influencers can shape the customer journey. They claim that from a marketing viewpoint, social media has started to influence every aspect of a consumer's decision-making process. Using two illustrative examples similar to then ones Appel et al. (2020, p. 82) use in their paper, show how social media can affect different stages of the consumer's decision-making process. (1) Scrolling through Instagram a consumer's favourite beauty influencer tries out a new shampoo and is highly satisfied, which activates the consumer's need recognition for this product. (2) On vacation, a consumer wants to try out a famous restaurant that he has heard of and engages in information search on Instagram watching videos of food influencers. These two examples show how touchpoints with social media influencers can influence different parts of a consumer's decision-making process, namely need recognition and information search. When companies now actively use influencers for promotion, the customer journey does not end here. These promotions usually embed influencer-specific links to the company's website or provide the customers with influencer-specific discount codes that they can use in their purchasing process (Beichert et al. 2024, p. 7). For a potential customer it is hard to tell whether the influencers' content is a reliable source of information or not (Li, Larimo, and Leonidou 2021, p. 79). An influencer's number of likes or followers can hereby serve as a signal for credibility and persuasiveness (Hamilton et al. 2021, p. 79).

These findings make it clear why marketers needed to reassess their strategy in the social media realm and already started to use online influencers for their marketing purposes. It remains a difficult task for marketers to identify the best way of online influencer marketing. On the one hand, marketers want to engage online influencers with a high follower count to have a broad reach for their marketing messages (Wies, Bleier, and Edeling 2023, p. 383). On the other hand, a high follower count does not necessarily result in the highest engagement. The findings of Wies, Bleier, and Edeling (2023, p. 401) assert an inverted U-shaped relationship between follower count and engagement, which shows that influencers with intermediate follower count seem to be more effective.

2.3 Customer Lifetime Value

The changing landscape in terms of technology and social media not only impacted the way companies approach marketing, but also opened new ways of collecting data and information about customers. Collecting transactional and survey data in times of smart phones, social media and e-commerce is easier than ever before (Sunder, Kumar, and Zhao 2016, p. 901). As a result, companies can utilize readily available customer data to conduct analyses and draw conclusions. The outcomes of such analyses provide especially high informative value for a company's customer relationship management. An effective outcome metric that proved itself is the so-called Customer Lifetime Value (CLV) (Sunder, Kumar, and Zhao 2016, p. 901). The CLV metric is a profitability-centered, forward-looking metric that assesses the long-term value of the customer base (Sunder, Kumar, and Zhao 2016, p. 918). Companies, in which CLV modeling served as the foundation for strategies and decision-making, were able to realize positive financial outcomes. This applies to the business-to-business (B2B) as well as the business-to-consumer (B2C) setting (Sunder, Kumar, and Zhao 2016, p. 901). Together with the fact that the market generally experiences a shift from product-centered to customer-centered marketing, CLV has grown to be a major metric used among many industries (Chan, Wu, and Xie 2011, p. 838).

From a marketing perspective, CLV is conceptualized as the net present value of cash flows generated by a customer and serves as an indicator of a customer's future profitability (Gupta, Lehmann, and Stuart 2004, p. 7; Zhang, Bradlow, and Small 2015, p. 195). There are several different practices of approaching the calculation of CLV throughout research literature. Without going into too much detailed comparison, every approach comes with its specific advantages and disadvantages. This paper follows an approach that has proven to generate significant results, which is the so-called RFM approach (Fader, Hardie, and Lee 2005, p. 426; Zhang, Bradlow, and Small 2015, p. 196). RFM stands for recency (R), frequency (F) and monetary value (M) (Zhang, Bradlow, and Small 2015, p. 195). In marketing, recency, frequency, and monetary value are means of summarizing a customer's prior purchasing behavior. Recency is defined as the most recent purchase of a customer, frequency as the number of prior purchases, and monetary value as the average price per transaction (Fader, Hardie, and Lee 2005, p. 415). These three variables are easily extractable from customer purchase data and are a sufficient base for further CLV calculations, what makes this approach flexible to use. The choice of this approach seems intuitive as it does not only provide significant results, but also incorporates three well-known concepts in marketing literature. There are also two other important inputs for CLV calculations that can be derived from the three initial variables of RFM. Firstly, the probability that a customer stays "alive", which represents the retention rate, and secondly, the monetary value the company can anticipate from the retained customer (Kumar et al. 2011, p. 924). Although CLV calculation methods might vary across marketing literature, they all aim to capture the same core concept outlined in this chapter.

To display the relevance and effectiveness of using CLV as an outcome metric, there are interesting results from two separate case studies. The first case study illustrates how IBM benefitted from applying CLV in their analysis for marketing resource allocation. IBM decided to apply a CLV-based marketing resource allocation strategy instead of their prior used allocation strategy. Because of that, IBM was able to increase its revenue by $20 million, which represented a tenfold increase without even increasing the marketing budget (Kumar et al. 2008, p. 585). The authors conclude that using a CLV-based approach can lead to an increased return on marketing investments due to the ability to better target customers that are likely to provide future value to the company. They further claim that after reallocating marketing investments based on CLV, a company can use its excess resources to grow and reactivate its customer base (Kumar et al. 2008, p. 596). The second case study shows similar results of applying a CLV-based approach of marketing resource allocation, but this time in a business-to-business (B2B) context. Venkatesan and Kumar (2004, pp. 106, 120) in their paper find that selecting customers based on CLV provides higher future profits for a company. A CLV-based allocation strategy compared to the status quo allocation resulted in an increase of net present value of future profits from $24 million to $44 million, an 83% increase (Venkatesan and Kumar 2004, p. 120). They also show that analyses based on CLV outperform analyses based on other commonly used metrics, such as PCR (previous-period customer revenue), PCV (past customer value), or CLD (customer lifetime duration).

These exemplary results highlight the growing interest in CLV-based analyses as such analyses can provide important and beneficial insights for marketers.

3. Customer Lifetime Value in E-Commerce: An Empirical Study

As previously discussed, influencer marketing has become a widely used marketing strategy with the potential of becoming even more important as the social media market tends to grow. This chapter now aims at empirically exploring the effects of influencer marketing in an E-Commerce context.

This chapter more specifically tries to shed some light on how influencers drive value for a company and if differential effects can be observed for different influencer classes, in terms of follower size. This study focuses on comparing customers acquired organically versus those acquired through influencers. Beyond the initial purchase, this chapter investigates the impact of influencer marketing on repeat purchases providing an in-depth examination of customer's purchase patterns. It entails the detailed investigation of monetary purchasing behavior of customers within these purchase patterns. In the following, whenever an 'organic purchase' is cited, it refers to a customer's purchase occurring naturally without the direct influence of an influencer, whereas 'influencer-driven purchases' are those directly assignable to an influencer. Lastly, the analyses employ the concept of CLV to provide marketers with further insights into customer value.

The following insights are gained by secondary sales data by one of Europe's leading Direct-to-Consumer (DTC) fashion firms. The dataset has been compiled by merging various sales data with only slight adjustments for cleaning, preserving its mostly raw nature. The characteristic of the resulting dataset is depicted in Table 1 ("Insert Table 1 about here"). It includes sales data of 1,479,838 customers, a total of 1,830,739 orders involving 3,370,619 individual items amounting for a total revenue of 753 million SEK before and 560 million SEK after discount. All monetary values in the following analyses are expressed in Swedish Krona (SEK). Additionally, the dataset includes information on whether customers used a discount code during their purchase. Some of these are influencer-related discount codes offering a great base for analysis as this makes influencer-related purchases of customers traceable (Leung, Gu, and Palmatier 2022, p. 247). These influencers are classified into five categories based on their follower counts, arranged from lowest to the highest: (1) nano-nano-influencers have 0-999 followers; (2) nano-influencers have 1,000-9,999 followers; (3) micro-influencers have 10,000-99,999 followers; (4) macro-influencers have 100,000-999,999 followers; and (5) mega influencers have 1,000,000 followers or more. In the analyses we differentiate between three different ways of customer purchases. Firstly, customers can make a purchase in a so-called organic way, which represents a normal purchase through the company's e-commerce store. Secondly, customers can make a purchase on the e-commerce store using an influencer-related discount code. And thirdly, the customers can make a purchase using a voucher code, which represents a discount code that is either issued by the company itself or that is not readily assignable to an influencer because of data inconsistencies.

3.1 Comparing Influencer-Driven and Organic Buying Behaviors

This chapter analyzes customers' purchasing behavior and explores whether there are specific purchase patterns that tend to stand out. Of particular interest is the comparison of organic purchases and purchases through influencers. Furthermore, it tries to identify customers or purchase patterns that provide the company with higher monetary value and high CLV.

3.1.1 Data. As previously mentioned, the data used for analysis originates from one of Europe's leading direct-to-consumer (DTC) fashion firms, which is very rich in information. Nonetheless, for the data to fit into the papers' research purposes some adjustments to the data have been made that can be seen by comparing the data from Table 1 and Table 2 ("Insert Table 2 about here"). The for the analysis chosen subset of data (see Table 2) only includes customers that have made at least two purchases over the past as relatively little insights can be gained by one-time purchases in terms of pattern analysis. This aligns with the goal of exploring the impact of influencer marketing on the whole customer journey, including the post-purchase phase and subsequent purchases. It includes sales data of 260,266 customers, a total of 611,112 orders involving 1,156,147 individual items amounting for a total revenue of ~257 million SEK before and a total of ~191 million SEK after discount. The focus of this analysis is the comparison between influencer-driven purchases and organically driven purchases. For that reason, purchases and patterns involving discount codes that are not assignable to an influencer are excluded. For simplicity, whenever 'type of purchase' is mentioned, it specifically refers to whether the purchase is influencer-driven or organically driven.

The dataset includes two variables for monetary values: 'price' and 'pricediscount'. At the item level, 'price' refers to the standard prices at which a company offers its items in the e-commerce store. In contrast, 'pricediscount' indicates the adjusted price of an item if a customer uses a discount code in their order. For each customer, the provided purchase data is then aggregated from the item level to the order level, ensuring that each order represents the total monetary value of the individual items. The customer's orders are then arranged from the earliest to the latest purchase and are labeled accordingly. For instance, the purchases of a customer who has made a total of three orders are coded as 'Purchase 1', 'Purchases 2' and 'Purchase 3'. The data is cleaned and organized in a way that for each individual purchase the type of purchase is readily available. For clarity, the type of purchase is coded as follows: an organic purchase is marked with the letter 'x'. If a purchase is influencer-driven, it is coded with the class attributed to the influencer, for example, 'mega-influencer' or 'nano-influencer'. Following this classification, a purchase pattern is coded as a concatenation of the purchase types without spaces. For instance, if a customer made two purchases, with the first being organic and the second being through a mega-influencer, the purchase pattern would be coded as 'xmega-influencer'.

3.1.2 Analysis. Differentiating and comparing purchase patterns based on a customer's initial purchase constitutes a very interesting area of investigation. The first purchase within a buying pattern can provide valuable insights into whether the customer was acquired in an organic or influencer-driven way. The rationale behind the chosen comparison structure is to gain insights into how influencer marketing might have influenced the customer journey as discussed in the theoretical background before. The benefit of analyzing purchase patterns is that it can additionally examine the effects of influencer marketing on repurchasing behavior. The analyzed data enables us to see whether a customer who made his first purchase through an influencer proceeds to make subsequent purchases with influencers or opts to organic repurchases instead. To increase the robustness and significance of the analyses, the data is separated into two cohorts that are then compared to one another. The first cohort consists of all customers that made their first purchase in the year 2020, whereas the second cohort consists of all customers that made their first purchase in the year 2021. These two cohorts are then further separated based on whether their first purchase was influencer-driven or organically driven. This allows for a comprehensive analysis and comparison based on purchase pattern characteristics for the two cohorts.

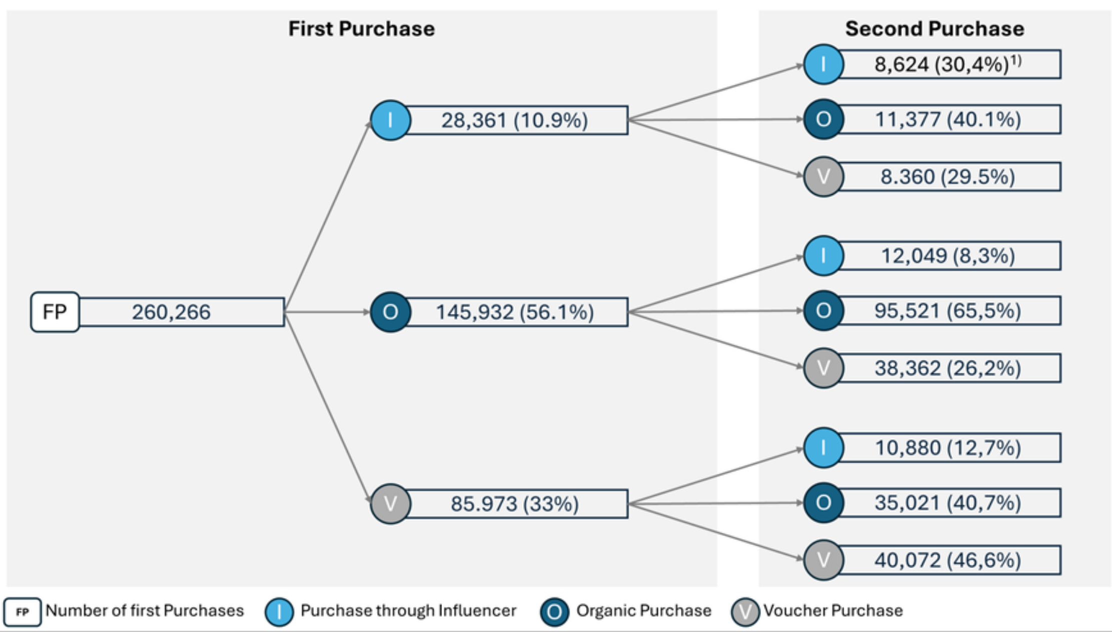
The analysis is structured in the following way. All customers within the two cohorts are separately clustered based on their purchase pattern characteristics. This means that all customers fall into the same subset in terms of purchase patterns if the following two prerequisites are met. (1) The customers made the same number of purchases in the analyzed timeframe. (2) The sequence of purchase types exactly matches. This means that all customers who have a purchase pattern of 'xmega-influencer' represent one subset, whereas customers with a pattern of 'mega-influencerx' represent another subset, as the order of purchase types differs. To gain meaningful insights, the following analysis then filters for the top ten of the most frequently observable purchase patterns within these subsets. These top ten patterns are then compared to one another based on the average monetary values per purchase, considering not only the price variable but also the pricediscount variable.

In addition to that, the analysis also includes an investigation regarding the interpurchase times of the top ten purchase patterns to gain valuable insights into the repurchase rates.

Lastly, the analysis also comprises the calculation and analysis of the metric Customer Lifetime Value (CLV) for every purchase pattern. As these purchase pattern subsets essentially represent customers with similar buying behavior, CLV can serve as an indication of profitability for these customer subsets. As discussed earlier, this paper applies the RFM approach for calculating CLV (Fader, Hardie, and Lee 2005, p. 415). The benefit from this approach is that all the necessary variables for calculating CLV can be derived from the provided datasets. The tools used for calculating CLV in our analysis stem from the ‘lifetimes’ package in Python. They are based on probabilistic models for customer behavior and use the variables recency, frequency, and monetary value to predict future purchase behavior and to calculate CLV (Kumar et al. 2011, p. 924).

3.1.3 Results. First, let us examine the distribution of purchase types among customers within the analyzed dataset. The customers within this dataset are segmented into two cohorts based on the criteria defined in the previous chapter. Figure 1 shows the percentages of customers who made their first purchases by one of the three previously described purchase types. It also depicts how customers based on their first purchase choose to make their second one. Figure 1 reveals that ~10.9% of customers made their initial purchase through an influencer and ~56.1% made their initial purchase in an organic way. Comparing second purchase percentages shows that customers who initially buy through an influencer are more likely to do so again (30.4%), compared to those who made their first purchase organically (8.3%). Most

Figure 1. Distribution of Type of Purchases for all Customers in the Dataset



1) Percentages of the second purchase are not calculated based on the total first purchases (18,175), but rather on the conditional purchases in the stage before (e.g., 9,991)

customers who initially buy in an organic way continue to do so with a percentage of ~65.5%. Subsetting the data into the two cohorts shows that out of the 102,940 customers in the 2020 cohort, 9,046 customers used an influencer for their first purchase, representing ~8.7% of the cohort. The 2021 cohort comprises a total of 49,275 customers of which 4,201 customers made an influencer-driven first purchase, representing 8.5% of the cohort. It is evident that across the two cohorts, the percentage of customers using an influencer for their first purchase remains relatively stable, accounting for a little less than ~10% of all customers. In absolute numbers, most customers tend to make their first purchase in an organic way.

Let us firstly analyze the customers whose initial purchases were made through an influencer. Table 3 shows a comparison of the top ten purchase patterns for the two cohorts, where customers used an influencer for their first purchase (2020 vs. 2021). For both cohorts, the left column shows the most frequently observable purchase patterns ordered from highest to lowest occurrence. The number of times these specific patterns occur among the cohorts is depicted in the second column. The first thing to notice is that the top ten patterns only involve two consecutive purchases, besides the pattern 'macro-influencerxx' that involves three consecutive purchases. Secondly, among the top ten of both cohorts, nine out of the ten purchase patterns are the same. Differing purchase patterns are highlighted in grey. Thirdly, the top three

Table 3. Overview of the Top 10 influencer-initiated Patterns

Top 10 Influencer-initiated Purchase Patterns			
Cohort 2020		Cohort 2021	
Purchase Pattern	Frequency	Purchase Pattern	Frequency
macro-influencerx	1299	mega-influencerx	1299
mega-influencerx	795	macro-influencerx	795
micro-influencerx	528	micro-influencerx	528
macro-influencermacro-influencer	450	mega-influencermega-influencer	450
mega-influencermega-influencer	291	macro-influencermacro-influencer	291
nano-influencerx	204	nano-influencerx	204
nano-nano-influencerx	192	micro-influencermicro-influencer	192
macro-influencermega-influencer	149	nano-influencernano-influencer	149
macro-influencerxx	146	macro-influencerxx	146
micro-influencermicro-influencer	129	macro-influencermega-influencer	129

patterns are identical among both cohorts, just ranked in a different order based on occurrence frequency. These results suggest that there appears to be a systematic pattern occurrence that cannot be solely attributed to randomness. Let us now also include customers into our findings that made their first purchase in an organic way. Table 4 now illustrates the top ten patterns for the two cohorts (2020 vs. 2021) when organically driven first purchases are added to the ones that are influencer driven, again ordered by occurrence from highest to lowest. Of these 102,940 customers from the first cohort, 60,283 customers made an organic first purchase, which represents about 58.6% of the whole cohort. In the second cohort, 30,271 customers of the total of 49,275 made their first purchase organically, which represents 61.4% of the total cohort. If we sum up the percentages of organically driven and influencer driven first purchases, we can see that they account for about 67% of the total cohort in 2020 and 70% of the total cohort in 2021. The remaining ~30% of customers made their first purchase either with a company-issued voucher code or with a code that cannot be allocated to an influencer and therefore, as previously mentioned, falls outside the scope of consideration. Across both cohorts, it can be observed that not only do the percentages match closely, but also that nine of the ten top patterns are consistent between them again. One noticeable difference when adding organic first purchases to the analysis is that within the top ten pattern 'xxxx' consisting of four consecutive

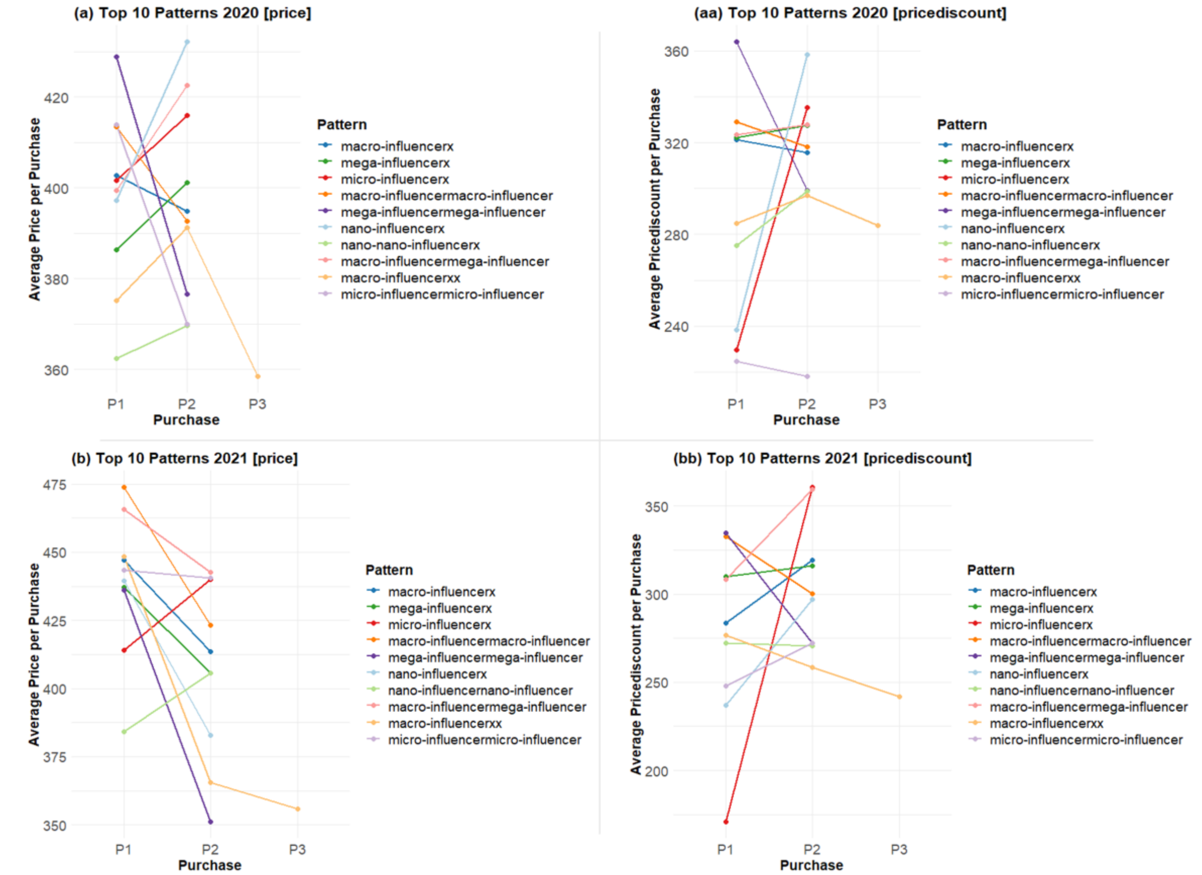
Table 4. Overview of the Top 10 Patterns Overall

Top 10 Purchase Patterns Overall			
Cohort 2020		Cohort 2021	
Purchase Pattern	Frequency	Purchase Pattern	Frequency
xx	30179	xx	18039
xxx	4477	xxx	2100
macro-influencerx	1299	mega-influencerx	553
mega-influencerx	795	macro-influencerx	539
xxxx	773	micro-influencerx	279
xmacro-influencer	683	xmega-influencer	271
xmega-influencer	657	mega-influencermega-influencer	264
micro-influencerx	528	xxxx	258
macro-influencermacro-influencer	450	xmacro-influencer	235
xmicro-influencer	305	macro-influencermacro-influencer	235

purchases whereas the maximum before were three consecutive purchases. It also becomes evident that patterns ‘xx’ and ‘xxx’, representing purely organic purchase behaviors, are by far the most frequently observed ones. However, from rank three onwards, influencer-driven purchases are very much present.

The following analysis illustrates additional insights for the previously identified purchase patterns among the two cohorts. The following figures present the average monetary values spent by customers on each consecutive purchase for the top ten purchase patterns. The x-axis depicts consecutive purchases (P1, P2, P3...), while the y-axis depicts the average amount of money spent per purchase for each pattern. Throughout the following discussion, ‘price’ and ‘pricediscount’ always refer to their respective average values. Connecting the dots for each pattern effectively illustrates the course of a customer’s average spending across their consecutive purchases and eases the comparison between them. Figure 2 presents four line graphs, illustrating the top ten purchase patterns where the first purchase was influencer-driven, separately for both the 2020 and 2021 cohorts. The two graphs (a) and (aa) show a comparison between the average price and the average pricediscount per purchase for the 2020 cohort, while the two graphs (b) and (bb) illustrate the same for the 2021 cohort. It is important to clarify that ‘pricediscount’, as previously defined, still refers to the adjusted price a customer pays after applying a discount code. Contrary, to what the term may imply, it does not indicate the discount amount obtained by a customer, but rather the actual price paid post-discount. Comparing both the average price metric and the pricediscount metric for the 2020 cohort in (a) and (aa), it is observed that generally the values of pricediscount are smaller in magnitude than the ones of price. This seems intuitive as, by definition, pricediscount should take values that are smaller or equal to the price, reflecting the reduced costs if a discount code is applied. It seems surprising at first that price and pricediscount values for purchases that are labeled with ‘x’ do not always match, despite indicating a transaction without a discount code. A plausible

Figure 2. Comparison of influencer-initiated Purchase Patterns



explanation for this might be that the company offered discounts on certain items via their e-commerce platform. These discounts could be reflected in the pricediscount metric (the price that customers actually pay for the product), but not in the price metric, which indicates the product's original listing price. Nevertheless, comparing both metrics, there are some interesting findings to point out. When we rank the patterns based on the magnitude of their monetary value, we can see that the ranking can shift from one purchase to another. For instance, it is observable that the pattern 'mega-influencermega-influencer' has the highest price value for the first purchase, but drops significantly for the second one. Another pattern involving an influencer class with the highest follower count for the initial purchase is 'mega-influencerx'. Interestingly, compared to other patterns, the first purchase only ranks in the middle, which signals that using a mega-influencer for the first purchase does not automatically result in the highest price value. Comparing it with 'micro-influencerx' that involves an influencer with a smaller follower count, we can see that in terms of price, 'micro-influencerx' exceeds 'mega-influencerx' for both purchases. However, for the comparison of pricediscount, 'mega-influencerx' generally ranks much higher, whereas 'micro-influencerx' only exhibits a higher pricediscount value for the second purchase. A possible explanation for this observation, especially for Purchase 1, could be a lower discount for mega-influencer related discount codes compared to other influencer-classes.

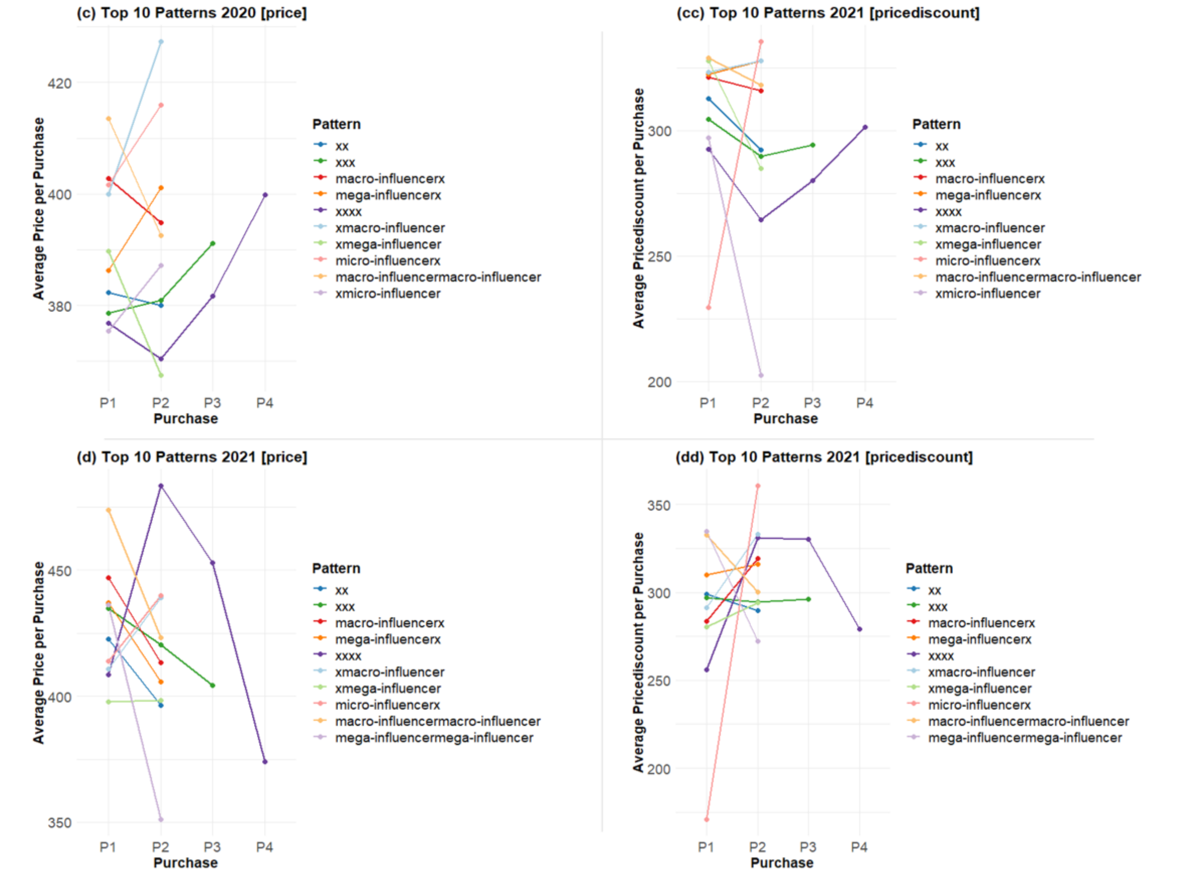
Proceeding with the same comparison but for the 2021 cohort in (b) and (bb) shows that the pricediscount values are generally lower than the price values again. Looking at (b), it is observable that the price value for the second purchase generally falls off compared to the first one. However, comparing it with the pricediscount values in (bb), this relationship seems reversed as there tends to be a pricediscount increase from the first to second purchase now. This could be due to initial purchases being made with influencer-related discount codes, resulting in smaller values, while many patterns' second purchases are organic, suggesting higher pricediscount values as no discount codes are used. An interesting observation for 'mega-influencermega-influencer' is that it ranks very low in terms of price compared to other patterns, whereas for pricediscount the first purchase represents the highest pricediscount value among all depicted patterns. Similar results are again observed for 'mega-influencerx'. This implies that in absolute terms, the discounts that were given by making a first purchase through mega-influencers tend to be lower than those for other influencer-classes, which also aligns with the findings for the 2020 cohort in (a) and (aa).

Comparing the results for the two cohorts reveals that the prices for the 2021 cohort tend to be higher than for the 2020 cohort. For some patterns like 'macro-influencermacro-influencer' this is especially noticeable for the first purchase. Another interesting observation is that the pattern 'macro-influencermega-influencer' takes relatively high price values in both cohorts, while being the only pattern in which there is a change of influencer-class from one purchase to another. All other purchase patterns in the top ten either involve a purchase through an influencer followed by an organic purchase or involve the same influencer-class for every purchase. Another quite striking observation can be seen by looking at 'macro-influencerxx', which is the only pattern that involves three consecutive purchases. In both cohorts 'macro-influencerxx' tends to score relatively low compared to other patterns, especially for the second and the third purchase. Taking a closer look at the pricediscount comparison in (aa) and (bb) the pattern 'nano-influencerx' reveals interesting insights. In both cohorts the pattern shows a very low pricediscount value for the first purchase, but this value significantly increases for the second one. For the 2020 cohort, it even reached the highest pricediscount value for the second purchase. In the 2021 cohort, the pricediscount value does not reach the highest rank compared to other patterns, attributable to a significant drop in the price value for the second purchase of 'nano-influencerx' in (b). As the pricediscount value is derived from the initial price value, the pricediscount thus tends to have lower values in (bb) as well. The pattern 'micro-influencerx' reveals similar characteristics with having a very low pricediscount for the first purchase that increases tremendously for the second one. Interestingly, the patterns showing a steep increase in pricediscount for the second purchase involve customers whose first purchase was made with influencers having a rather small follower count, such as nano-influencers and micro-influencer.

Let us now also take patterns into consideration that involve a first purchase that is driven organically. Figure 3 presents four line graphs again, illustrating the top ten purchase patterns where the first purchase is now either influencer-driven or organically driven, separately for both the 2020 and 2021 cohorts. The structure of comparison and the graphical illustration is like in the analysis before. The two graphs (c) and (cc) show a comparison between the average price and the average pricediscount per purchase for the 2020 cohort, while the two graphs (d) and (dd) illustrate the same for the 2021 cohort.

Comparing the first purchases for each pattern in the 2020 cohort in (c) reveals that the price value seems to be generally higher when first purchases are made through influencers. It

Figure 3. Comparison of Purchase Patterns Overall



is observable that purchase patterns that start with an influencer driven purchase such as 'macro-influencerx', 'mega-influencerx', or 'micro-influencerx' tend to have higher price values for their initial purchases than those patterns that have an organically driven first purchase like 'xx', 'xxx' or 'xmicro-influencer'. We also find that this relationship between influencer driven and organically driven first purchases extends to the second purchase, where higher price values are observable for patterns where the first purchase is made through an influencer. Overall, this relationship tends to be consistent, except for 'xmacro-influencer', which shows relatively high price values for both purchases, despite its first purchase being organically driven. Looking at the pricediscount metrics in (cc) reveals similar results. Again, patterns like 'macro-influencerx' or 'mega-influencerx' show relatively high pricediscount values for both purchases whereas patterns like 'xx' or 'xmicro-influencer' exhibit lower pricediscount values. Influencer driven first purchases therefore also show higher pricediscount values than patterns with organically driven first purchases. An exception represents the pattern 'xmega-influencer', which demonstrates high pricediscount values for both purchases. Moreover, an interesting observation emerges from contrasting price and pricediscount values for the pattern ‘micro-influencerx’. The first purchase of this pattern represents the third highest price value within the top ten patterns, whereas for pricediscount it ranks last. This suggests that customers who made purchases through micro-influencers achieved significant discounts by using micro-influencers’ discount codes. This observation is supported by a similarly steep decrease in the pricediscount value for the second purchase of ‘xmicro-influencer’, where customers again used a micro-influencer but this time for their second purchase.

Graphs (d) and (dd) for the 2021 cohort depict the same patterns except for ‘xmicro-influencer’, which is replaced by the pattern ‘mega-influencermega-influencer’ within the top ten. Similar results as the ones described for the 2020 cohort before are observed when comparing the price values among the patterns in (d). Patterns that involve a first purchase through an influencer score higher in terms of price value than those of which the first purchase involves an organic purchase. The four highest price values for first purchases are all part of an influencer-initiated purchase pattern, of which two of these patterns exclusively involve influencer-related consecutive purchases, namely ‘macro-influencermacro-influencer’, and ‘mega-influencermega-influencer’. All four patterns are either initiated through a mega- or a macro-influencer, representing those influencers with the highest follower count. An additional observation for these patterns is that the price value of the second purchase always tends to be lower than the price for the initial purchase. Looking at organically driven first purchases, it is revealed that they tend to be generally lower in price values than influencer driven ones. This relationship is however not so clear for patterns like ‘xxx’ or ‘xxxx’ consisting of only organically driven consecutive purchases or ‘xmarco-influencer’ consisting of an influencer driven second purchase. Especially for the second purchase, the price values of these pattern exceed the influencer-initiated purchase patterns. An outstanding pattern here is ‘xxxx’ with four consecutive organic purchases that shows exceptionally high price values for the second and third purchase, which then drop drastically for the fourth purchase though.

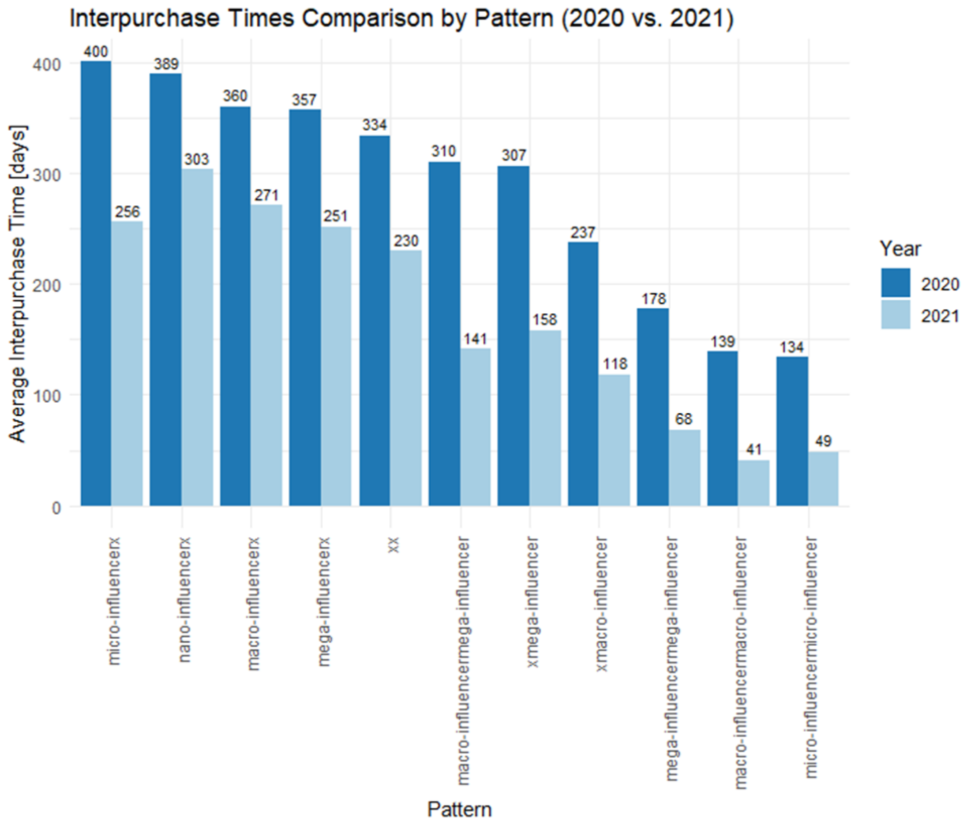
When we now investigate the course of purchasing behavior for the pricediscount values in (dd), it is notable that the three highest first purchase pricediscount values are by influencer-initiated patterns. These are the same patterns that previously showed the highest price values, though this time excluding 'macro-influencerx', which has a rather mediocre pricediscount value for its first purchase. However, the second purchase for 'macro-influencerx' is again one of the higher values of pricediscount. Like the findings from the price comparison before, some organically initiated patterns like 'xmacro-influencer' or 'xxxx' exceed second purchase pricediscount values of influencer-initiated patterns. Nevertheless, this is not confirmable for every organically initiated pattern as patterns like "xx" or "xxx" show lower pricediscount levels than other influencer-initiated patterns. This is a noteworthy finding because typically the pricediscount value of an organic purchase is expected to be higher than that of a purchase made through an influencer. This stems from the assumption that influencer-related discount codes should lead to a further reduction in the pricediscount value compared to an organic purchase made without discount code. Another intriguing observation is the relatively low pricediscount value of the first purchase of 'micro-influencerx', followed by a steep increase for the second purchase, representing the highest pricediscount value for any second purchase. The low pricediscount value for the first purchase ought to result from a high discount that customers received by using a micro-influencer's discount code.

As before, we now not only want to compare the results within the cohort but also across the two cohorts to identify significant findings. Let us firstly compare the two cohorts along their price values. The only patterns that are not comparable are 'xmicro-influencer' and 'mega-influencermega-influencer', as these are the patterns in which the top ten differs. The top ten patterns among the two cohorts mostly involve two consecutive purchases, except for 'xxx' and 'xxxx'. Both patterns represent purely organic purchases, whereas most other purchases within the top ten at least include one purchase made through an influencer. It is noticeable that 'xxxx' in the 2020 cohort rather ranks towards the lower end in terms of price value, especially for purchases 1 to 3, exhibiting a u-shaped trend that increases from the second purchase onwards. Conversely, within the 2021 cohort, the price values are notably higher, representing an inverted u-shape with a peak at the second purchase and subsequent decline. The primary objective of this paper is to investigate potential differential effects between organic buying behavior and influencer driven buying behavior. Therefore, the focus will be on comparing 'xx' with the other patterns that involve at least one influencer driven purchase. This comparison seems logical as 'xx' is particularly comparable to patterns involving influencers because both mainly consist of two consecutive purchases. By looking at the two cohorts, it becomes apparent that there are several purchase patterns for both cohorts that involve an influencer related purchase at some point, that perform better in terms of price value. For both cohorts, the influencer-initiated purchase patterns 'macro-influencerx', 'mega-influencerx', 'macro-influencermacro-influencer' perform better than 'xx' on both purchases. Compared to 'xx', patterns that involve an organic first purchase like 'xmacro-influencer' exhibit higher price values for both purchases in the 2020 cohort (c) and a higher price value for the second purchase in the 2021 cohort (d). Differing results are observable when comparing the two cohorts in terms of their pricediscount values in (cc) and (dd). Compared to 'xx', the two patterns 'macro-influencermacro-influencer' and 'mega-influencerx' are now the only ones displaying higher pricediscount values for both purchases in both cohorts. Even though not consistent across both cohorts and both purchases, 'xmacro-influencer' shows relatively high pricediscount values compared to the pattern 'xx'. Another insightful finding is that 'micro-influencerx' in both cohorts has a very low pricediscount value for its first purchase but then exhibits a tremendous increase for the second purchase. This confirms the previous assumption that customers who used a micro-influencer discount code received a substantial discount on their initial purchase. It also suggests that customers tend to spend more on the subsequent purchase after using a micro-influencer on their first, as the values of the second purchases exceed those of ‘xx’.

These findings show that compared to solely organic purchasing behavior, purchasing behavior that involves influencers can have a positive effect on the monetary values spent on consecutive purchases. The results suggest that influencers with large follower count like mega-influencers and macro-influencers, but also influencer with a smaller follower count like micro-influencers can positively affect customer spending.

Previously, it was illustrated that most of the observed purchase patterns among the top ten consisted of two consecutive purchases. Therefore, it is interesting to further explore whether there might be differences between the interpurchase times within these patterns involving two consecutive purchases. Interpurchase time is hereby defined as the time between a customer’s first and second purchase, measured in days. Figure 4 now collectively illustrates the interpurchase times of both influencer-initiated and organically initiated purchase patterns within the top ten. The analysis excludes patterns that are not present in both the 2020 and 2021 cohort to ensure the significance of observed pattern findings. The dark blue bars represent the interpurchase time for patterns in the cohort of 2020, whereas the light blue bars represent the interpurchase time for the cohort of 2021. Firstly, it is apparent that the interpurchase times for the 2021 cohort are consistently shorter than those for the 2020 cohort. This aligns with expectations, as the observation period for the 2021 cohort is generally shorter than the one for the 2020 cohort. There are three organically initiated purchase patterns, of which ‘xx’, with two consecutive organic purchases, has the longest interpurchase time among the three. The longest interpurchase times are observed for patterns patterns with an organically driven second purchase (e.g., ‘micro-influencerx’ or ‘xx’), whereas shorter interpurchase times are observed for patterns involving an influencer-driven second purchase (e.g., ‘xmacro-influencer’ or

Figure 4. Comparison of Interpurchase Times



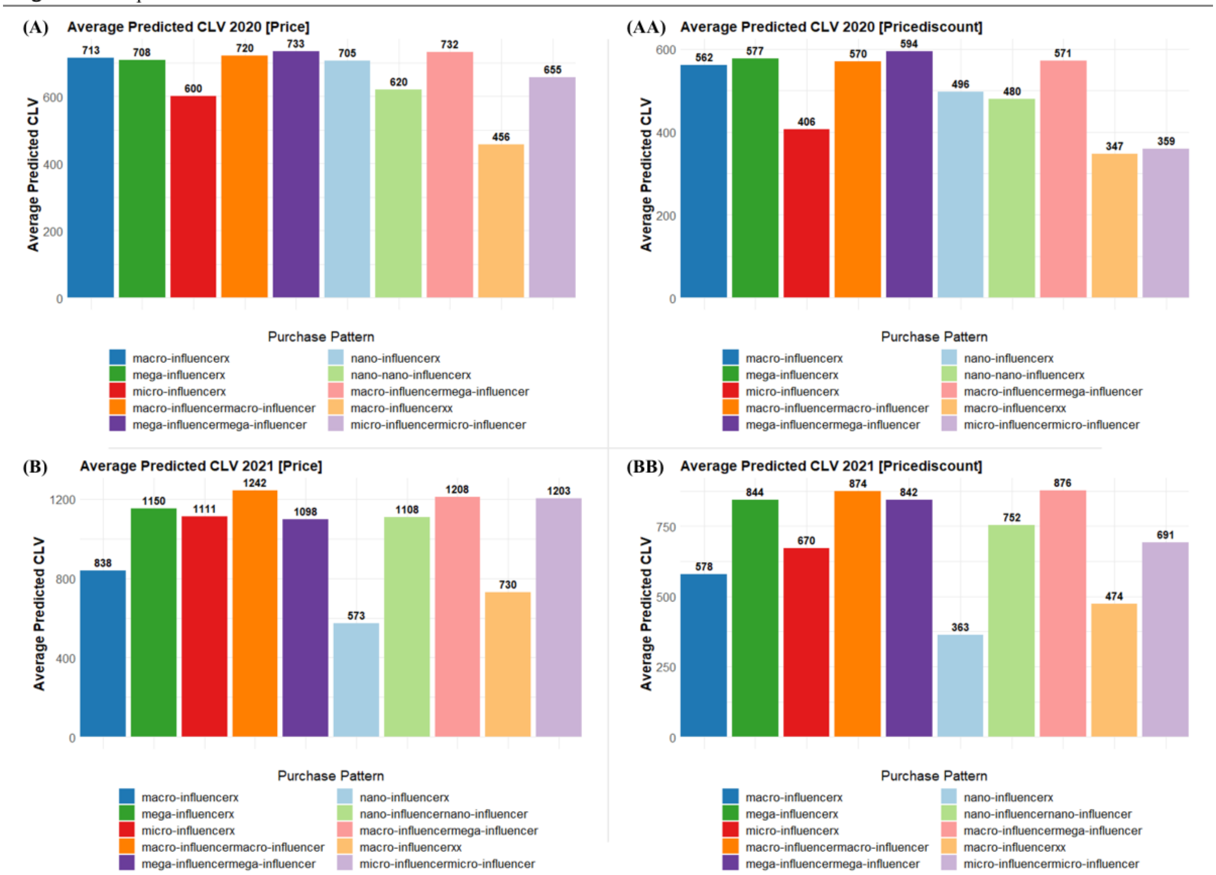
'micro-influencermicro-influencer'). Notably, this relationship is consistent across all the purchase patterns presented. There are only four patterns in which both purchases are made through an influencer, and only three of them feature the same influencer-class. An insightful finding is that the three shortest interpurchase times among all patterns are observed for patterns featuring two consecutive purchases made through influencers of the same influencer class. This raises the question what percentage of customers used the exact same influencer for both consecutive purchases in the patterns 'mega-influencermega-influencers', 'macro-influencermacro-influencer' and 'micro-influencermicro-influencer'. In the 2020 cohort, 297 of the 450 customer who made both of their purchases through a mega-influencer chose the same influencer for both transactions. This represents 66% of the customers in this pattern. In 2021 the percentage rises to 85% as 200 out of 235 customers chose the same influencer. Within the 2020 cohort, approximately 77% (224 out of 291 customers) made a consecutive purchase through the same mega-influencer, and 88% (234 out of 264 customers) in the 2021 cohort, indicating a notable increase. Similarly, for micro-influencers, 71% (92 out of 129 customers) in the 2020 cohort and 89% (101 out of 113 customers) in the 2021 cohort ended up choosing the same micro-influencer for both purchases, further highlighting a trend of choosing the same influencer for consecutive purchases. These findings show that most customers choose the same influencer for consecutive purchases if both purchases are within the same influencer class. This tendency also seems to increase even more.

Drawing on these findings, it can be concluded that interpurchase times can be shortened when customers pursue an influencer-driven purchase after their initial purchase. This explicitly includes cases in which both purchases are influencer-driven as it can further decrease interpurchase time if the influencer is within the same influencer-class. A possible explanation for these relationships might be that customers are motivated to repurchase sooner when exposed to a promotion by an influencer they follow, effectively reactivating their recognition of need. In contrast to that, for an organic repurchase, the trigger for repurchase might be missing.

Let us now look at how the different patterns compare in terms of Customer Lifetime Value. The CLV is calculated based on recency, frequency, and monetary value for each pattern. Each pattern's CLV is then depicted through bar charts where both price and pricediscount serve as inputs for the monetary value. For our CLV calculations the BG/NBG and Gamma-Gamma-Model are used, which base their future purchase predictions on the frequency, recency and monetary value of past purchase behaviors. As depicted earlier, most patterns only involve two consecutive purchase points. With, on average, only two past purchase data points, the predictive nature of the model is quite limited, and results must be taken with caution due to the limited data richness regarding the number of consecutive purchases. Another factor potentially affecting the significance of our CLV calculations is raised by Zhang, Bradlow, and Small (2015, pp. 306–207). They found that not accounting for the factor 'clumpiness' in addition to RFM can significantly impact the predictive value of the model. They define clumpiness as a phenomenon where customers tend to make multiple purchases in a short period of time, followed by periods of inactivity (Zhang, Bradlow, and Small 2015, pp. 196, 206–7). This could serve as an indication for our mediocre model fit as clumpiness is not specifically added to our calculations. The following results thus rather serve an illustrative nature and can in combination with the prior findings lead to interesting implications.

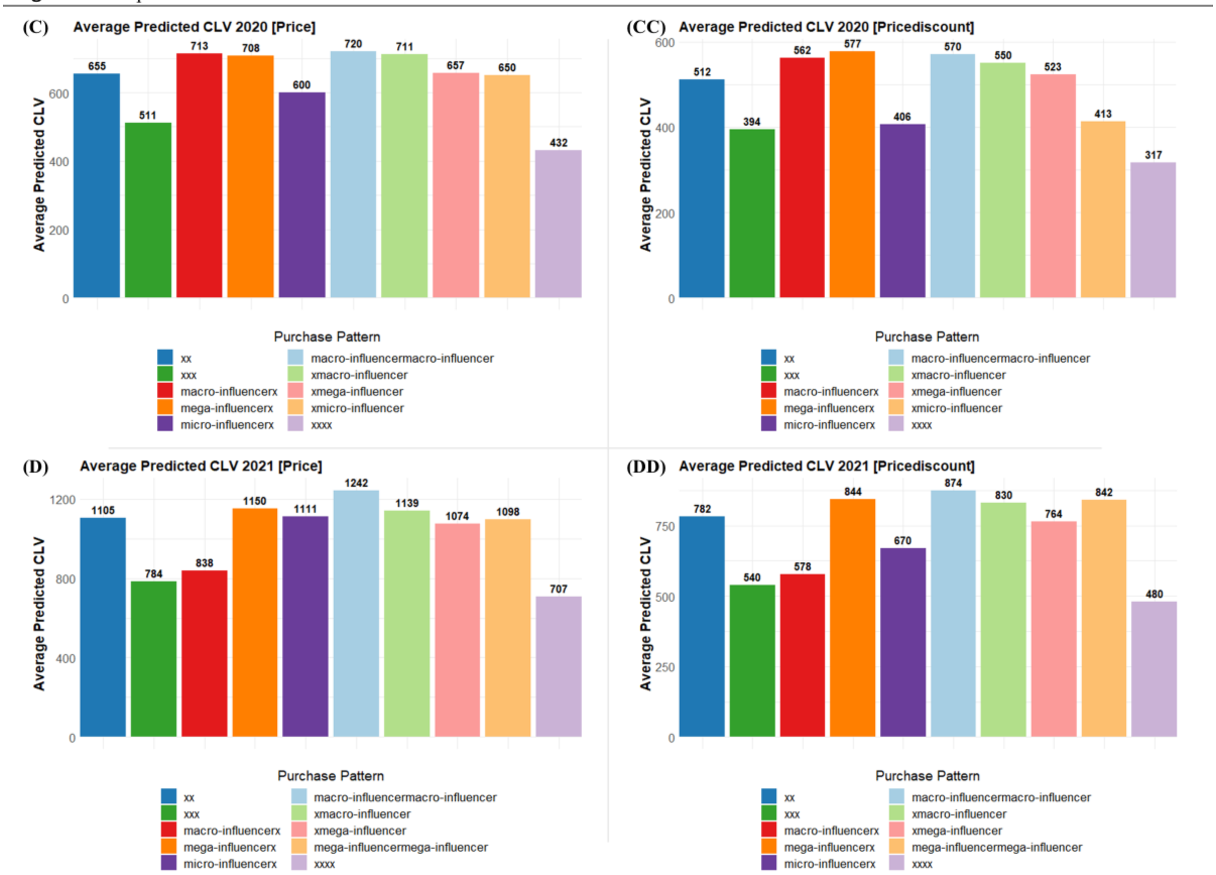
Figure 5 provides a comparison of CLV for influencer-initiated purchase patterns among the 2020 and 2021 cohorts. The CLV comparison based on price for the 2020 cohort is depicted in (A) and (AA), whereas the comparison for the 2021 cohort is shown in (B) and (BB). Notably, patterns such as 'macro-influencermacro-influencer', 'mega-influencermega-influencer' and 'macro-influencermega-influencer' demonstrate consistently high CLV, considering both the price and pricediscount metrics. All three patterns involve two consecutive purchases through influencers and, as previously highlighted, are characterized by very short interpurchase times.

Figure 5. Comparison of CLV influencer-initiated Purchase Patterns



Another pattern with significantly low interpurchase times is ‘micro-influencermicro-influencer’, which ranks relatively high in CLV when evaluated using the price metric. However, a noticeable decrease in CLV is observed when considering the pricediscount metric. This decline may be attributed to the significant discounts, customers received when using a micro-influencer discount code for their purchases, which in turn reduces the monetary values used for the CLV calculation. Figure 6 now also takes the organically driven first purchase patterns into consideration. The only patterns including more than two consecutive purchases are ‘xxx’ and ‘xxxx’, consisting of only organic purchases. Both rank significantly lower than other patterns considering the price and pricediscount metric. Taking ‘xx’ as a baseline for comparison allows us to compare the impact of influencer-driven purchases relative to organic purchases. We can see that, patterns involving at least one influencer-driven purchase tend to score higher or comparable CLVs than ‘xx’, except for the pattern ‘macro-influencerx’ in the 2021 cohort. This deviation may be attributed to the low average price and particularly low

Figure 6. Comparison of CLV for Purchase Patterns Overall



pricediscount value for the first purchase in this pattern, as depicted in Figure 6. Patterns that stand out across both cohorts are ‘macro-influencermacro-influencer’, ‘xmacro-influencer’, and ‘mega-influencerx’. These findings suggest that patterns involving at least one influencer related purchase score higher CLV values, especially for the influencer classes of mega- and macro-influencers.

In conclusion, these analyses illustrate several noteworthy results. They suggest that there appears to be a systematic pattern occurrence that is not solely attributed to randomness. As shown, influencer-related purchases compared to organic purchases offer positive effects such as higher purchase values and shorter interpurchase times. It is further demonstrated that there are interesting relationships for influencers with a small follower base, who offer substantial discounts for the first purchase but experience a tremendous increase in value for the second purchase.

3.2 Analysis of High Value Customers

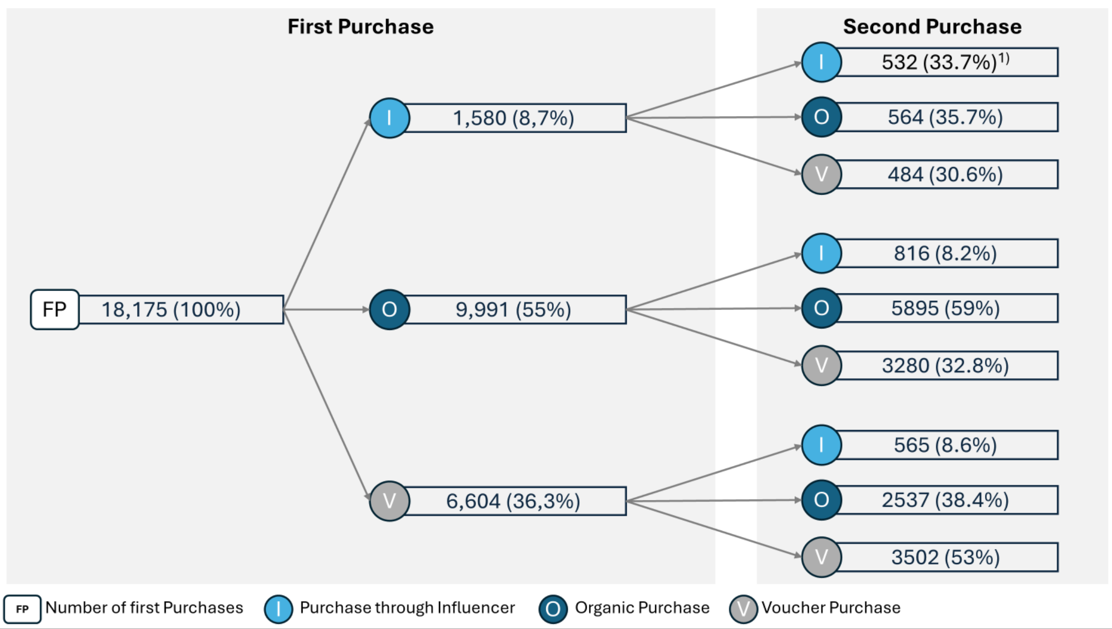
Whereas the previous chapter examined and analyzed characteristics among the whole customer base, this chapter specifically analyzes whether there are differential effects observable for high value customers. This chapter tries to shed some light on the purchase pattern characteristics of customers that contribute to a company’s revenue more than others. It is, additionally, analyzed how influencers might drive value for this specific customer group.

3.2.1 Data. Our analysis focuses on customers that drive a company’s revenue more than other customers. We define high value customers as those contributing to the top 20% of a company’s revenue, with the price metric serving as the basis for this calculation. Therefore, high value customers are those that spend the most amount of money among their purchases. Using the price metric as the basis for calculating that threshold provides us with insights on a company's top-line revenue. We identify high value customers in our dataset the following way. Firstly, we calculate a customer's total spending across all consecutive purchases in terms of price. Secondly, we sort the customers by their highest spending and then group them into a subset such that their combined spending amounts to ~20% of the company's total revenue. This effectively gives us the highest value-providing customers in monetary terms over the whole dataset, accounting for ~51.4 million SEK of the total revenue of ~257 million SEK over the observation period (January 2019 – May 2023). As in the previous analysis, the data is aggregated from item to order level and for each purchase it is readily observable whether the purchase was made in one of the three possible ways: (1) organic, (2) influencer-driven, (3) through company-issued voucher code or a code that cannot be attributed to an influencer.

3.2.2 Analysis. In the subsequent analysis, it is firstly examined through which of the three purchase types, high-value customers engaged with the company on their first purchase. As the focus of this paper is to determine and compare the impact of influencer-driven purchases with organic purchases, customers who made purchases with non-influencer related vouchers have been excluded from the analysis. We firstly analyze the distribution of influencer classes with which high-value customer make their first purchases. We secondly illustrate how many times an influencer-specific discount code on average was used based on their associated influencer class. To also being able to compare the results to the findings before, we then subset the data again into the two cohorts of 2020 and 2021. Subsetting the two cohorts is based on the same rules that we applied in our analysis before, except that it is applied to the dataset of high-value customers. Following a similar approach as before, we then further investigate the most commonly observable purchase patterns for these high-value customers examining the effects of influencer-driven and organically driven purchases. We distinguish between influencer-initiated and organically initiated purchase patterns among both cohorts. We lastly touch on the topic of CLV.

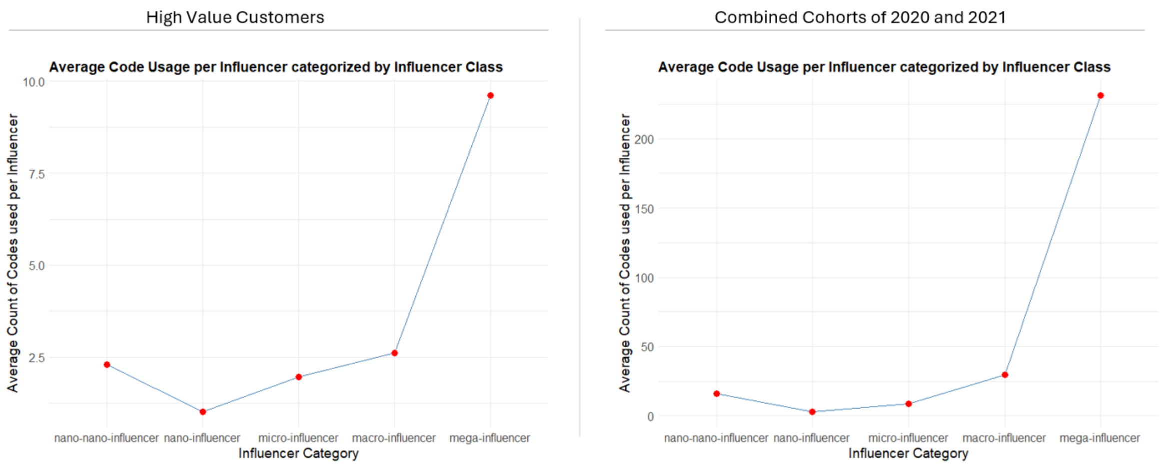
3.2.3 Results. The first notable finding is that out of the initial dataset (see Table 2) which totaled 260,266 customers, only 18,175 customers are accountable for generating the top 20% of the company's revenue. That means that only ~7% of customers are responsible for 20% of the company's revenue. When we now look at Figure 7, we can see how these customers differ in the type of their first and second purchase. About 8.7% of high value customers made their first purchase with an influencer, whereas ~55% of customers chose to make their first purchase in an organic way. Comparing second purchase percentages shows that customers who initially buy through an influencer are more likely to do so again, compared to those who made their first purchase organically. Interesting results become apparent when we look at the average number of times a discount code was utilized for every influencer within a given class. In the left graph of Figure 8 we can see that the distribution follows a u-shaped curve from lowest to highest follower count. It is surprising to find that codes associated with nano-nano-influencers are used more frequently on average than those of nano-influencers and micro-

Figure 7. Distribution of Type of Purchases – High Value Customers



1) Percentages of the second purchase are not calculated based on the total first purchases (18,175), but rather on the conditional purchases in the stage before (e.g., 9,991)

Figure 8. Average influencer-related Code Usage per Influencer on Influencer-Class



influencers and almost macro-influencers, who have a larger follower count and, arguably, a broader reach. On the other hand, mega-influencers show, by far, the highest frequency of average code usage among all influencer classes. Linking back to the theoretical findings, a possible explanation for this could be that influencers like nano-nano-influencers with a smaller follower count have a closer relationship with their followers enhancing purchasing behavior (Beichert et al. 2024, pp. 16–17). To additionally check if this relationship holds true for the whole cohort or if this distribution is unique to high value customers, the same analysis is done in the right graph of Figure 8 but for the whole 2020 and 2021 cohort from chapter 3.1. The results confirm the u-shaped relationship.

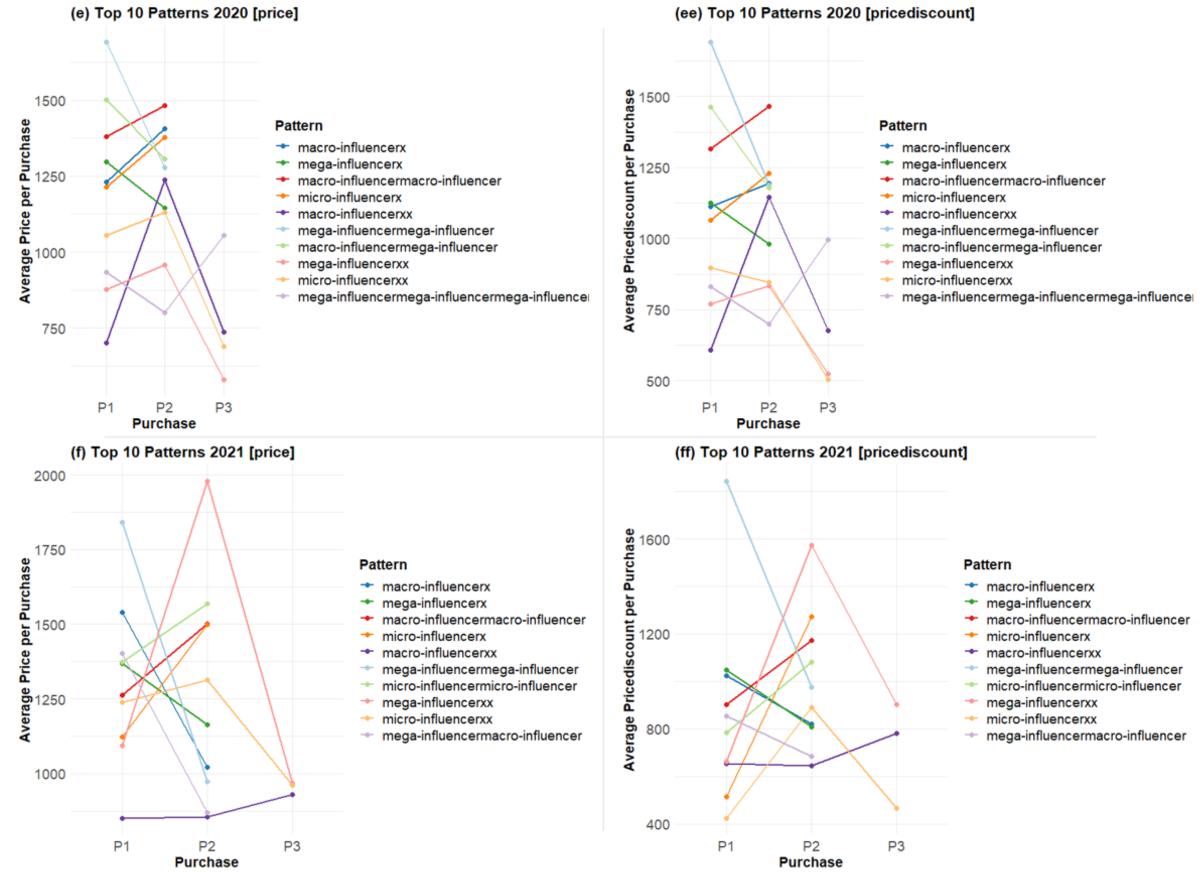
The following presents the results of the comparison of purchase patterns between the two cohorts. The 2020 cohort comprises of 6,009 customers, while the 2021 cohort consist of 2,981 customers. Let us start by looking at influencer-initiated purchase patterns. Within the two cohorts, Table 5 depicts the top ten most frequently observed patterns among both cohorts when the first purchase involved an influencer. By looking at the pattern overview, we can see that most patterns are the ones that we also observed in the previous chapter. A notable new pattern is the one for the cohort of 2020 that involves three consecutive purchases with mega-influencers. However, the observed frequency with 6 out of 418 influencer-initiated purchase patterns is relatively low. This needs to be considered when analyzing the results of this analysis

Table 5. Overview of the Top 10 influencer-initiated Patterns - High Value

High Value Customers - Top 10 Influencer-initiated Purchase Patterns			
Cohort 2020		Cohort 2021	
Purchase Pattern	Frequency	Purchase Pattern	Frequency
macro-influencerx	25	mega-influencerx	27
mega-influencerx	23	macro-influencerx	16
macro-influencermacro-influencer	18	macro-influencermacro-influencer	14
micro-influencerx	14	micro-influencerx	13
macro-influencerxx	11	micro-influencermicro-influencer	7
mega-influencermega-influencer	10	mega-influencermega-influencer	6
macro-influencermega-influencer	9	mega-influencerxx	5
mega-influencerxx	8	mega-influencermacro-influencer	4
micro-influencerxx	7	macro-influencerxx	4
mega-influencermega-influencermega-influencer	6	micro-influencerxx	3

as the sample size is relatively small compared to the one we had in the analysis before. Nonetheless, the pattern analysis can provide us with meaningful insights. Similarly to the analyses before, let us firstly look at Figure 9 which depicts the top ten patterns of both cohorts based on the price metric and pricediscount metric. On the one hand, by looking at (e) and (f), there are more patterns within the top then that involve three purchases. On the other hand, most of the influencer-initiated patterns for high-value customers still constitute only two consecutive purchases. It gives the impression that high-value customers not necessarily purchase more often, but rather that the individual prices per purchases are much higher. Compared to the average prices of the analysis in chapter 3.1, we can see up to an approximately fourfold increase of purchase prices per order for high-value customers (e.g. for 'macro-influencermacro-influencer'). This implies that at least for influencer-initiated purchase patterns, the monetary value spent per purchase appears to be the main driver of revenue rather than the frequency of buying. It also appears that the highest initial prices for patterns with two consecutive purchases are reached with influencers of the class mega-influencer and macro-influencer. A surprising outlier is the second purchase in the 'mega-influencerxx' pattern for the 2021 cohort. This purchase shows the highest average price value compared to all other patterns, despite having a relatively low average price in the 2020 cohort. This outlier is attributed to the second purchases of two customers, one ordering five items and the other six items, significantly inflating the average price due to the small sample size of five customers

Figure 9. Comparison of influencer-initiated Purchase Patterns – High Value



within this pattern. Comparing the patterns based on pricediscount in (ee) and (ff) reveals similar results to those observed for the price metric. Neglecting the outlier of 'mega-influencerxx' in the second purchase for cohort 2021, it becomes evident that purchase patterns with three consecutive purchases seem to generally have lower pricediscount values than those patterns consisting of two consecutive purchases.

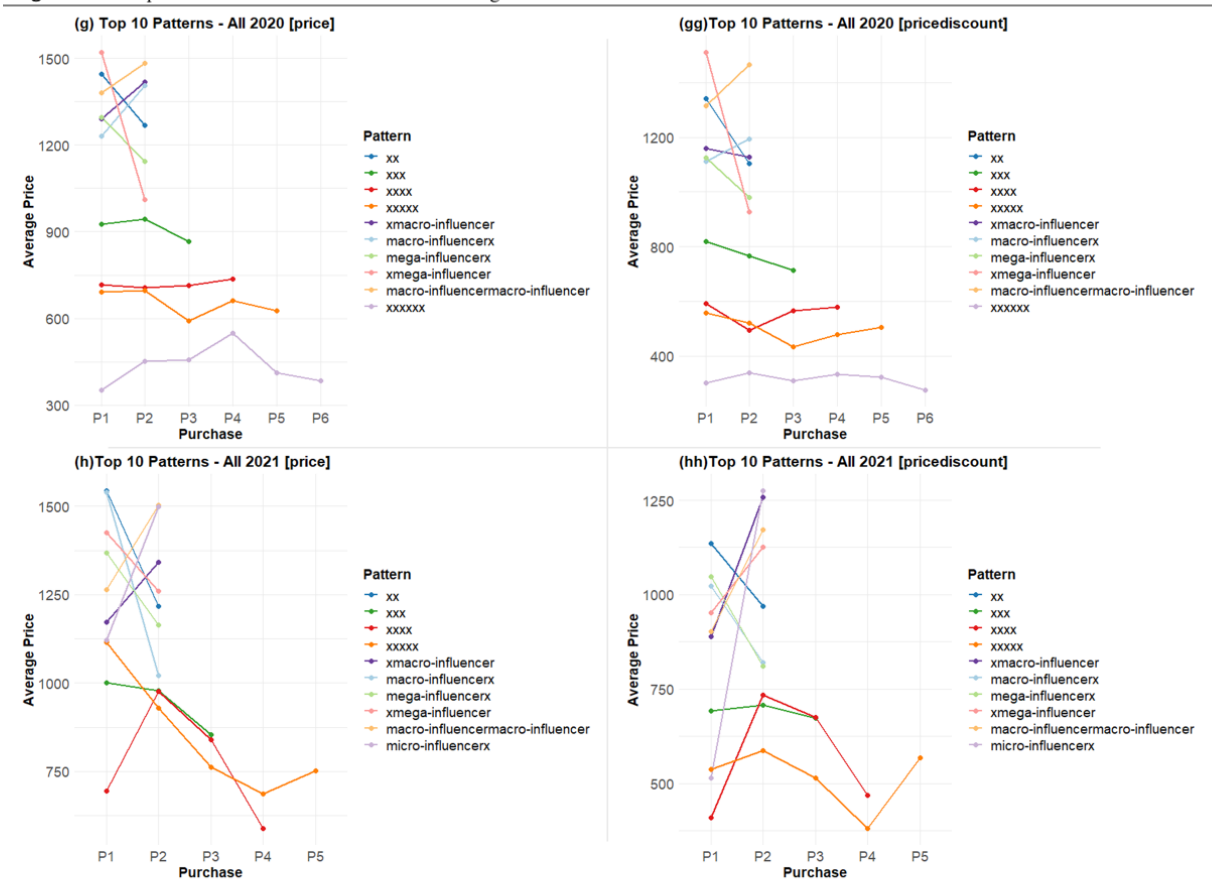
If now organically driven first purchases are added for consideration, we can see significant changes within the top ten most frequently occurring patterns, depicted in Table 6 and Figure 10. We can see that four to five out of the top ten are patterns involving only organically driven consecutive purchases. It is also the first time that there are purchase patterns within the top ten that involve more than four purchases. By looking at (g) and (h), it appears that purchase patterns that involve more than two consecutive purchases have lower individual purchase prices than the ones with only two consecutive purchases. This relationship holds true for both influencer-initiated as well as organically initiated purchase patterns. We previously

Table 6. Overview of the Top 10 Patterns Overall - High Value

High Value Customers - Top 10 purchase Patterns Overall			
Cohort 2020		Cohort 2021	
Purchase Pattern	Frequency	Purchase Pattern	Frequency
xx	782	xx	661
xxx	362	xxx	248
xxxx	129	xxxx	64
xxxxx	49	mega-influencerx	27
xmacro-influencer	30	macro-influencerx	16
macro-influencerx	25	xxxxx	14
mega-influencerx	23	macro-influencermacro-influencer	14
xmega-influencer	18	micro-influencerx	13
macro-influencermacro-influencer	18	xmega-influencer	10
xxxxxx	15	xmacro-influencer	10

derived the assumption for influencer-initiated purchase patterns that the monetary value rather than the purchase frequency seems to be the main driver for revenue within the high-value customers. This relationship holds true for influencer-initiated purchase patterns, but needs to be refined when taking organic purchase behaviors into consideration. As we can see in Table 6, most high-value customers engage in purely organic purchasing behaviors. Examining the

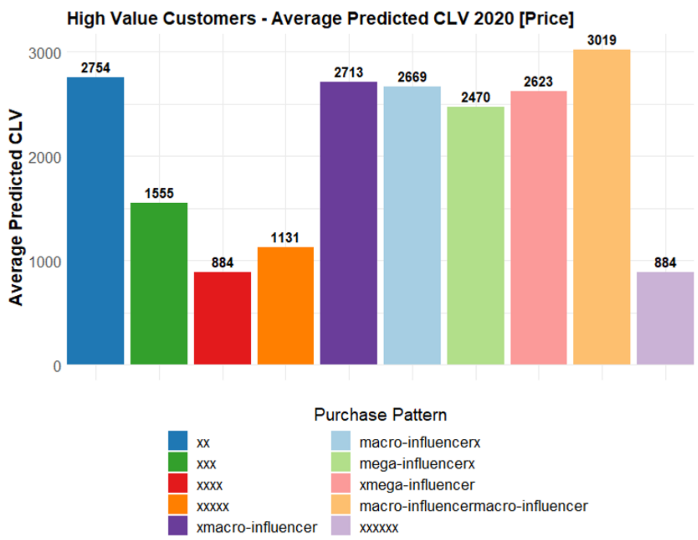
Figure 10. Comparison of Purchases Patterns Overall – High Value



price values in (g) and (h), it becomes clear that the main driver of revenue for purely organic patterns involving more than two consecutive purchases (e.g. ‘xxx’, ‘xxxx’…) is not the price magnitude of each individual purchase. Instead, it is the frequency of consecutive purchases and the cumulative total of all purchases. Although having lower price values for individual purchases, their cumulative total contributes significantly to overall revenue. Nonetheless, compared to ‘xx’ being a purely organic purchase pattern, patterns that also involve two purchases, of which at least one is made through an influencer, exhibit comparably high price values. Similar results are observed by looking at (gg) and (hh) in Figure 10 comparing the pricediscount values. Interestingly, for the 2021 cohort, there is a significant drop in the first purchase for ‘micro-influencerx’ for both the price and pricediscount metric. This can probably be attributed to the fact that customers who used a micro-influencer were able to receive significant discounts on their purchases. This would be in line with the finding from the previous chapter where we observed similar behaviors.

Lastly, this analysis only illustrates the exemplary CLV results for the 2020 cohort incorporating the top ten patterns for organically and influencer driven purchases. The calculation and depiction are the same as we previously showed in chapter 3.1. These results again need to be viewed with caution as there is limited model fit and a very small sample size

Figure 11. CLV Comparison for High Value Customers – Cohort 2020



for many patterns. It is thus only depicting the results exemplary for one cohort to potentially provide some interesting implications for further investigation in future research. The preliminary results from Figure 11 show that the CLV seems to significantly decline for purchase patterns involving more than two consecutive purchases. A potential explanation for this phenomenon might be that, even though customers tend to buy more often, the monetary value spent per purchase is extremely low compared to customers that only have two consecutive purchases (see Figure10). Another explanation could be that customers who already made more than two purchases are less likely to purchase again, which therefore reduces their future value for the company.

In can be concluded that influencer-related purchases also have positive effects on high-value customers. An interesting characteristic is that for patterns with two consecutive purchases, individual spending per purchase appears to drive revenue. However, for patterns with more than two purchases, it is the frequency of buying, as the individual price values per purchase are lower.

4. Discussion

The last chapter provides a critical assessment of both the findings and the data analyzed. It also outlines some managerial implications arising from this study. Finally, limitations and potential future research directions are presented.

4.1 Critical Evaluation

This empirical study tries to shed light on the effects of influencer marketing on Customer Lifetime Value. Even though the analyzed data is very rich in information, there are several aspects that need to be viewed with caution. The aim of this study was to analyze and depict the customer data as representative as possible without hurting the data population. However, numerous data points of the raw dataset had to be excluded due to inconsistencies or illogical values, such as instances where pricediscount values exceeded the actual price values. As the analysis of influencers is of particular interest in this empirical study, it needs to be noted that many voucher codes were not assignable to influencers, even though their labeling would suggest an influencer-related discount code. Additionally, influencers were then categorized based on their influencer classes for further analysis. However, the categorization to an influencer class was not always possible as for many influencers the data regarding their follower count was unavailable. Considering these issues that cause influencers to drop out of the analysis scope led to a general undervaluation of the impact of influencers on purchasing behavior in terms of absolute numbers. Nevertheless, to derive and ensure significant results, underestimating the effects of influencers is preferable to overestimating their effect.

4.2 Managerial Implications

There are numerous interesting implications for marketers that can be derived from this empirical study. This paper illustrated that there are significant patterns across customers' purchasing behavior when it comes to organically driven and influencer driven purchase sequences. We observed that influencer-driven purchases compared to organic purchases can come with several benefits such as higher monetary spending behavior. We also found that customers using an influencer for their second purchase show significantly shorter interpurchase times. Interpurchase times are especially low for those customers who decide to use an influencer for both subsequent purchases. Adding to that, most customers who buy through the same influencer class on subsequent purchases, pursue their purchase with the exact same influencer. As a result, based on the strategic goals of marketers, they might be able to use influencer marketing as a mean to trigger faster repurchasing behavior among customers.

Analyzing and clustering customers' purchasing behavior can thus help marketers to potentially analyze when and how to approach specific customers with influencer marketing measures to effectively drive sales. Lastly, we showed that even though most customers still engage in organically driven purchases, many customers already choose to purchase through influencers. Considering the growing online influencer market, the percentage of influencer-driven purchases suggest to grow even further. This paper also indicates that marketers should not underestimate influencers with smaller follower count as the engagement, in terms of average code usage per influencer-class, exhibited a u-curved function, revealing smaller influencers to be more efficient in some cases.

In conclusion, this paper provides interesting implications for marketers but also highlights the challenges associated with analyzing customer purchasing behaviors to derive meaningful conclusions.

4.3 Limitations and Future Research

Even though this thesis provides interesting insights for marketers in terms of influencer marketing and their effects on a customer's spending behavior, there are several limitations. The analyses in this paper in terms of influencer classification is solely based on the follower count. It does not include the individual characteristics of an influencer in terms of what content they produce on social media or on how they market the company's offerings. Additionally, this paper only considers the revenue generation aspect, but neglects the costs associated with influencer marketing, such as for paid advertisements. Taking the cost side into consideration might have interesting implications on the effectiveness of influencer marketing, especially if larger influencers like mega-influencers are getting paid more than smaller influencers. This could potentially make smaller influencers even more appealing in terms of cost-benefit analysis. We showed that the average code usage exhibits a u-shaped curve, making smaller influencers more efficient in this sense. Building upon the findings of Beichert et al. (2024, pp. 16–17) and integrating them with the purchase pattern analysis suggested in this paper represents a promising area for future research. The last limitation of our analysis comes with the provided data structure. The model fit and predictive value of our CLV calculation suffer from the fact that most customers only made two consecutive purchases in the past. Our results therefore rather serve as an indication of potential effects while also providing opportunities for future research in this area. As outlined by Zhang, Bradlow, and Small (2015, pp. 206–7), future research in this direction should consider adding clumpiness to the analysis scope. This may improve model fit and enable more meaningful implications to be derived from the CLV analyses.

Tables

Table 1: Data Overview for Cleaned Dataset

Table 1. Data Overview for Cleaned Dataset

Variable Name	Description	Sum	Mean	Median
Total Sales SEK (price)	Total Revenue generated through sales in (Mean and median on order level)	752,781,205.14	411.19	303.22
Total Sales SEK (pricediscount)	Total Revenue generated through sales discounts deducted (Meand and median on order level)	560,337,764.11	306.07	199.5
Customers	No. of customers in the dataset who made a sale on the e-commerce platform; Mean and median calculated based on price [pricediscount] per customer	1,479,838	508.69 [378.65]	349 [232.86]
Orders	No. of total orders in the dataset. Each order can involve several Products/items (Mean and median calculated per customer)	1,830,739	1.24	1
Products	Number of total items sold (Mean and median on Order level)	3,370,619	1.84	1
Voucher Code	No. of total voucher codes used on Order level (excl. Influencer related discount codes)	495,663		
Influencer Code	No. of total influencer-related discount codes used on Order level	217,151		
nano-nano-influencer	No. of unique nano-nano-influencers in the dataset [No. of discount codes used associated with nano-nano-influencers]	263 [4,708]	17.9	2
nano-influencer	No. of unique nano-influencers in the dataset [No. of discount codes used associated with nano-influencers]	3,291 [11,029]	3.4	2
micro-influencer	No. of unique micro-influencers in the dataset [No. of discount codes used associated with micro-influencers]	1,580 [18,670]	11.8	2
macro-influencer	No. of unique macro-influencers in the dataset [No. of discount codes used associated with macro-influencers]	566 [38,521]	68.1	10
mega-influencer	No. of unique mega-influencers in the dataset [No. of discount codes used associated with mega-influencers]	37 [31,365]	847.7	331

Table 2: Data Overview for Customers with at least two Consecutive Purchases

Table 2. Data Overview for Customers with at least two Consecutive Purchases

Variable Name	Description	Sum	Mean	Median
Total Sales SEK (price)	Total Revenue generated through sales in (Mean and median on order level)	257,040,384.75	420.60	306.82
Total Sales SEK (pricediscount)	Total Revenue generated through sales discounts deducted (Meand and median on order level)	191,241,498.57	312.93	199.5
Customers	No. of customers in the dataset who made a sale on the e-commerce platform; Mean and median calculated based on price [pricediscount] per customer	260,266	987.61 [734.79]	788.63 [535.28]
Orders	No. of total orders in the dataset. Each order can involve several Products/items (Mean and median calculated per customer)	611,122	2.35	2
Products	Number of total items sold (Mean and median on Order level)	1,156,147	1.0	1.0
Voucher Code	No. of total voucher codes used on Order level (excl. Influencer related discount codes)	206,072		
Influencer Code	No. of total influencer-related discount codes used on Order level	71,309		
nano-nano-influencer	No. of unique nano-nano-influencers in the dataset [No. of discount codes used associated with nano-nano-influencers]	127 [1,345]	10.6	2
nano-influencer	No. of unique nano-influencers in the dataset [No. of discount codes used associated with nano-influencers]	1,666 [3,524]	2.1	1
micro-influencer	No. of unique micro-influencers in the dataset [No. of discount codes used associated with micro-influencers]	903 [5,722]	6.3	2
macro-influencer	No. of unique macro-influencers in the dataset [No. of discount codes used associated with macro-influencers]	429 [11,897]	27.7	6
mega-influencer	No. of unique mega-influencers in the dataset [No. of discount codes used associated with mega-influencers]	36 [9,767]	271.3	87.5

Appendix

Appendix A: Comparative Literature Review Table

	Theoretical Background		Customer Journey		Customer Lifetime Value	
Citation	Social Media	Influencer Marketing	Concept	Influencer Impact	Conceptualization	RFM
This thesis	x	x	x	x	x	x
Appel et. al (2020)	x	x				
Beichert et. al (2024)	x	x				
Chan, Wu, Xie (2011)					x	
Chen (2017)			x			
Fader, Hardie, Lee (2005)					x	x
Grewal et. al (2018)			x			
Grewal et. al (2020)	x	x	x	x		
Gupta, Lehmann and Stuart (2004)					x	
Hamilton et. al (2021)	x	x	x	x		
Knoll and Matthes (2017)			x			
Kumar et. al (2011)					x	
Kumar et. al (2008)					x	x
Lemon and Verhoef (2016)			x	x		
Leung et. al (2020)						
Leung, Gu and Palmatier (2020)	x	x	x	x		
Fangfang, Larimo and Leonidou (2021)	x	x	x	x		
Sunder, Kumar, and Zhao (2016)					x	
Venkatesan and Kumar (2004)					x	
Wies, Bleier and Edeling (2023)	x	x	x	x		
Zhang, Bradlow and Small (2015)					x	x

Appendix B: Literature Review Tables[1]

Author/s (Year) *[Journal]*	**Research Focus**	**Theoretical Background**	**Sample**	**Method/Analysis**	**Main Findings**
Appel et. al (2020) [*Journal of the Academy of Marketing Science*]	The future role of social media in marketing	Definition of Social media Omni-social presence Online Influencer marketing		Theoretical	Online Influencer Marketing leverages an influencers' unique resources to promote a firm's offerings Content of online influencers appears more authentic, making it easier to nudge customers Online influencers represents a cheaper marketing action for smaller firms than celebrity endorsements

[1]The literature review tables (pp. 46-56) may contain direct citations from the respective sources shown in the first column

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Beichert et. al (2024) [*Journal of Marketing*]	Revenue Generation Influencer Marketing	Influencer Marketing Social media Paid endorsements Return on Investment Social capital theory	Secondary sales data of 1,881,533 purchases	Total-effect model with secondary sales data IV: number of followers DV: revenue per follower CV: Several control variables Mediation analysis to test indirect effects, two parallel mediators: • follower engagement • influencer engagement Three field studies with hundreds of paid influencer endorsements to provide robustness for superior performance of low followership targeting	• Influencers with lower follower count outperform influencers with higher follower count on three ROI metrics • Most profitable influencer type is nano-influencer in realm of DTC firms

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Chan, Wu, Xie (2011) [*Marketing Science*]	Measuring the value of customers acquired from Google Search Advertising	Customer Lifetime Value Customer acquisition Search Advertising	Web traffic and sales data from small-sized US firm (sample period 2004 to 2007)	Pareto/NBD model for customer lifetime (1) Modelling value of 67 new customers acquired from Google (2) Comparison with 341 customers acquired from other channels	• Higher transaction rate for customers acquired from Google Search advertisement • Development of a framework to evaluate long-term profit impact of search advertising investments
Chen (2017) [*Journal of Consumer Research*]	Differing WOM based on friends or strangers	Word of mouth Consumer behavior Social acceptance		Seven studies Examining two distinct WOM factors: • Valence • Self-memory	• People share different WOM with strangers versus friends • Positive WOM preferred for self-enhancement (strangers) • Negative WOM preferred for emotional connection (friends)

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Fader, Hardie and Lee (2005) [*Journal of Marketing Research*]	Customer Base Analysis using Iso-Value Curves (RFM and CLV)	Customer Lifetime Value (CLV) Recency, Frequency, Monetary Value Pareto/NBD framework Gamma-gamma submodel	n = 23,570 people making first purchase at CDNOW	(1) CLV conceptualization based on stochastic model, RFM, Pareto/NBD and gamma-gamma model (2) Holdout tests to show validity of model components (3) Calculation of CLV for cohort of new customers for online music site CDNOW	• Significant benefits of RFM inputs for CLV calculation as easily extractable from customer characteristics •
Grewal et. al (2018) [*Journal of Marketing*]	Customer Purchasing Behavior	Mobile Shopping Limited Attentional Capacity Theories Distraction Literature	Store area of 36,140 square feet Field study: n = 393 participants Field experiment: n = 121 participants	Field Study 1: • Eye-Tracking Study of In-Store Shopping • Participants asked to shop as usual Field Experiment 1: • Eye-Tracking Study in two grocery stores • Participants asked to shop as usual • Serial mediation model capturing consumers distraction levels	Unlike suggested, mobile phone use increases point-of-purchase sales, reasons are: • Customers divert from shopping loop • Spend more time in store • Spend more time on examining price and products

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Grewal et. al (2020) [*Journal of the Academy of Marketing Science*]	Future trends of technology and marketing	Technology in marketing Consumer behavior		Theoretical	• Smart phones have altered daily routines of consumers • Permanent interaction with mobile devices, social media throughout the day • Engage in transactions through mobile apps and web
Gupta, Lehmann and Stuart (2004) [*Journal of the Academy of Marketing Science*]	Customer Value for companies Customer Lifetime Value	Customer Valuations Discounted future Cash Flows	n = 5 firms Quaterly data from annual reports 10-K, 10-Q and reports from 1996-1997 to March 2002	• Value of a firm's customer as the sum of lifetime value of current and future transactions • Model estimation with data from five companies: Capital One, Amazon, Ameritrade, eBay, E*Trade • Quaterly data from annual reports	• Valuing customers makes it possible to value firms • A 1% increase in retention has almost 5 times greater impact on firm value than a 1% change in discount rate or cost of capital

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Hamilton et. al (2021) [*Journal of Marketing*]	The role of social others within the Customer Journey	Customer Journey Social influence Social media Online Influencers		Theoretical	• Opinion leaders of the past increasingly replaced by social media influencers • Identity signaling through social media easier than in offline setting • Increasing number of brands actively managed social influencers • Important for companies to evaluate when to engage in Customer Journey to nudge customers from evaluation to purchase
Knoll and Matthes (2017) [*Journal of the Academy of Marketing Science*]	Assessing the effectiveness of celebrity endorsements	Cognitive effects Affective effects Behavioral effects Celebrity endorsements	Data from three major databases n = 1025 articles (300 of them quantitative studies) n=46 studies for meta-analysis (10,357 participants)	Meta-analysis	• No effect when averaging across all studies • Including moderator variables, attitude and behavior effects strongest when male actor matches endorse object • Generally, celebrity endorsements worse for endorsements of quality seals, awards, endorser brands

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Kumar et. al (2011) [*Marketing Science*]	Relationship between a customer's transaction value and Customer Lifetime Value and marketing activity	Transaction value of customers Customer Lifetime Value Hidden Markow model	B2B transaction data from July 1999 to June 2004	• Estimation of demand model • Computation of optimal resource allocation conditional on demand parameters • Hidden Markov Model	• In B2B context, the relationship between transaction value (relationship state) and lifetime value can be nonmonotonic • Marketing expenditures are nonmonotonic, highest expenditure is not automatically best for high value customers
Kumar et. al (2008) [*Marketing Science*]	Customer Lifetime Value – Case Study IBM	Customer Scoring Metrics Customer Lifetime Value Marketing expenditure	n = 35,000 customers	• Measurement of CLV (NPV of cash flows over 36 months) • Comparison of Traditional Customer Selection Metrics with CLV • Definition of Allocation Strategy • Resource Reallocation • Field Study of contacting customers with high CLV predictions for future	• CLV-based resource allocation led to a tenfold increase in revenue without increasing marketing expenditure • CLV based approaches can help: ○ Increase marketing ROI ○ Identify products to sell as bundles ○ Reallocate excess resources

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Lemon and Verhoef (2016) [*Journal of Marketing*]	Touchpoints throughout the Customer Journey	Customer Behavior Customer Experience and Customer Journey Marketing strategy		Theoretical	Conceptualization of the Customer Journey in three dynamic phases: • Prepurchase phase • Purchase phase • Postpurchase phase Recent focus on touch points within customer journey broadens marketing thinking of companies Companies need to manage several touchpoints within customer journey
Leung et. al (2020) [*Journal of Marketing*]	Effectiveness of Influencer Marketing	Influencer Marketing Marketing effectiveness Consumer engagement Social Media	n = 5,835 influencer marketing posts n = 2,412 online influencers (rel. to 1,256 campaigns for 816 brands in October 2018)	(1) Creation of communication model framework (2) Model test with data provided by marketing platform in china	• Influencers posting more original content are more effective • Follower size enhances effectiveness • Influencer marketing allows for crowdsourcing of influencer’s follower network, content, personal positioning and follower trust

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Leung, Gu and Palmatier (2022) [*Journal of the Academy of Marketing Science*]	Online Influencer Marketing (OIM)	Online influencer marketing Social capital theory Marketing communication		Theoretical	• OIM defined as leveraging influencer resources to enhance firm's marketing effectiveness • Small influencers are cheap and effective alternative to expensive celebrity endorsements • Trust benefits of influencers can transfer to brand-related trust • Technological advancements allow for analyses of performance metrics like influencer-specific coupons
Fangfang, Larimo and Leonidou (2021) [*Journal of the Academy of Marketing Science*]		Social Media Marketing strategy Customer engagement		Conceptualization of the development process for social media marketing strategies (SMMSs), comprising four components • Drivers • Inputs • Throughputs • Outputs	• Social media transformed the way customers and firms interact • Social media value comes from generating connections (social media use along provides no value) • Companies must accommodate customers' motivations for using social media

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Sunder, Kumar and Zhao (2016) [*Journal of Marketing Research*]	Lifetime Value of Customers	Customer Lifetime Value (CLV) Customer Relationship Management (CRM)	Data for carbonated beverages for n = 40,098 customers	Framework to assess CLV Bayesian estimation	• Strategies for CRM that are developed from CLV modelling led to positive financial gains in both B2B and B2C settings • CLV metric is heavily dependent on customer relationships and transaction data
Venkatesan and Kumar (2004) [*Journal of Marketing*]	Customer Lifetime Value Framework for Customer Selection and Resource Allocation Strategy	Customer Lifetime Value (CLV) Resource allocation strategies	Data from multinational computer hardware and software manufacturer Cohort 1 (first purchase in first quarter 1997) Cohort 2 (first purchase in first quarter 1998)	CLV Function including: • Purchase frequency • Contribution margin • Marketing costs	• Selecting customers based on CLV provides higher future profits than selecting based on other metrics • A CLV-based resource allocation resulted in 83% increase in revenue

Author/s (Year) ***[Journal]***	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Wies, Bleier and Edeling (2023) [*Journal of Marketing*]	The effect of follower count on social media engagement	Influencer marketing Social media engagement	Field data: n = 801 Instagram marketing campaigns with n > 1700 influencers	Observational field data analysis Eye-tracking study Laboratory Experiments	• Higher follower counts have broader reach but also weaker engagement likelihood • Influencers with larger indegree might lack resources or interest to engage in meaningful relationships with followers • Reliance on smaller influencers can provide benefits
Zhang, Bradlow and Small (2015) [*Marketing Science*]	Customer Lifetime Value	Customer Lifetime Value RFM Clumpiness	n = 42,000 randomly selected customers	CLV calculation with RFM, adding clumpiness (RFMC) Application of C to seven different datasets	• RFM are sufficient input variables for calculating CLV and scoring customers • Clumpiness contributes significantly to profiling customers and calculating CLV • Clumpiness is widely spread on the Internet • RFM can lead to prediction errors if clumpiness is not captured and it exists

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