Driving Conversions: Banner Performance Analysis

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1 Executive Summary

This report provides an in-depth analysis of user behaviour and banner performance for an online sporting goods store. By examining how users interact with banners and understanding their retention and conversion patterns, this analysis highlights critical areas for optimisation. Using exploratory data analysis, cohort analysis, funnel analysis, and A/B testing, actionable recommendations are presented to improve user engagement, retention, and sales performance.

1.1 Key Findings

1. **Understanding user behaviour:**

    - Mobile users account for over 70% of interactions but have a significantly lower conversion rate (CVR) than desktop users.
    - Desktop users exhibit stronger purchase intent, achieving a CVR more than twice that of mobile users.
    - Despite higher click-through rates (CTR) on mobile, fewer clicks result in purchases, indicating challenges in mobile user conversion.

    These findings underscore the need to optimise the user experience on both platforms to cater to their distinct behaviours.

2. **Retention trends:**

    - Retention analysis is essential for evaluating whether banners succeed in fostering repeat engagement, a key goal for sustained campaign effectiveness.
    - Retention rates drop significantly after the first month, stabilising at 14–17%, far below industry benchmarks.
    - Repurchase rates decline sharply after the first month, highlighting the need for stronger long-term engagement strategies.

    This analysis demonstrates the importance of addressing early-stage drop-offs to maximise user lifetime value.

3. **Funnel insights:**

    - While the overall CVR from banner show to purchase is 6.6%, exceeding industry averages, major drop-offs occur at each funnel stage.
    - Desktop funnels reveal inconsistencies, with orders exceeding banner clicks due to traffic sources like direct visits or ad-blocking issues.
    - Product performance varies, with clothes achieving a CVR of 9.5%, far outperforming underperforming categories like accessories and sports nutrition.

    Funnel analysis highlights areas where targeted interventions can reduce drop-offs and improve the effectiveness of the user journey.

4. **Time-based conversions:**

- Conversion rates remain stable across weekdays but peak sharply during late-night hours (22:00 to 03:00), exceeding 20%.

These insights emphasise the importance of timing and visibility in campaign strategy.

1.2 Recommendations

1. **Optimise user experience across platforms:**
   - Simplify the mobile checkout process and offer exclusive promotions for mobile users to boost conversions.
   - Redesign desktop banners to increase engagement and address tracking inconsistencies caused by ad blockers.
2. **Strengthen retention strategies:**
   - Improve onboarding for new users during the critical first month with targeted incentives and loyalty programmes.
   - Re-engage inactive users through personalised email campaigns and gamified features to sustain interest.
3. **Tailor marketing by product performance:**
   - Adapt successful strategies from high-performing categories like clothes to underperforming ones, while accounting for differences in user preferences.
   - Offer bundled discounts or personalised recommendations to boost sales in lower-performing categories.
4. **Leverage timing insights:**
   - Prioritise banner displays during late-night peak hours (22:00 to 03:00) to maximise conversions.
5. **Investigate user pathways:**
   - Conduct deeper analysis of traffic sources to identify user pathways and resolve discrepancies in desktop funnels.

By addressing the identified challenges and implementing these recommendations, the business can better understand and cater to user behaviours, improve long-term retention and conversions, and enhance the performance of banner campaigns across platforms and product categories.

2 Introduction

The online store focuses on selling sporting goods such as clothing, shoes, accessories, and sports nutrition. To boost sales, the store uses banners on its main page that randomly promote different products. These banners are designed to grab users' attention and encourage them to make purchases.

The marketing team believes that the success of these banners can vary depending on the types of customers and how they interact with the site. Analysing these interactions can help the store understand what drives users to click on banners and complete purchases.

This report focuses on the following business goals:

- Analyse how customers interact with banners on the website.
- Identify key factors that influence purchase decisions and banner performance.
- Use different analysis techniques, including cohort analysis, funnel analysis, and A/B testing, to explore user behaviour in detail.
- Provide recommendations to improve banner performance and increase sales.

By addressing these goals, the store can better understand its customers and make informed decisions to improve sales and customer satisfaction.

3 Exploratory data analysis (EDA)

The data has three main features: product category (clothes, sneakers, nutrition, accessories), user platform (mobile, desktop), event type (banner show, banner click, order). Let us look at the distribution of events across these features (table 1).

Product		**Platform**		**Event**	
clothes	26.5	mobile	72.2	banner show	86.2
sneakers	25.2	desktop	27.8	banner click	10.1
nutrition	24.2			order	3.7
accessories	24.0				

Table 1: Distribution of events across products, platforms, and event types.

Each product category accounts for approximately 25% of the total number of events, indicating a balanced distribution across products. More than 70% of users access the platform via mobile, showing a strong preference for mobile over desktop. The banner click rate is relatively low at around 10%, and the purchase rate is even lower at about 4%, showing an imbalance in the target data.

Having examined the overall event distribution across features, we now turn to an analysis of conversion rates (CVR) by time. Understanding how CVR fluctuates by weekday and hour provides valuable insights into user behaviour.

The first chart (fig. 1) shows that conversion rates remain relatively consistent across weekdays, fluctuating only slightly around 4%. This suggests that user purchasing behaviour is stable throughout the week, with no specific day standing out as significantly better or worse for conversions.

The second chart (fig. 2) shows a clear pattern in hourly conversion rates, with a sharp peak between 22:00 and 03:00, reaching over 20% at its highest. Conversion rates drop significantly during standard working hours, only beginning to rise again in the late evening.

Given the strong performance during the late-night hours, it would be beneficial to focus banner displays during the 22:00 to 03:00 window. This strategy could help target users at times when they are more likely to convert.

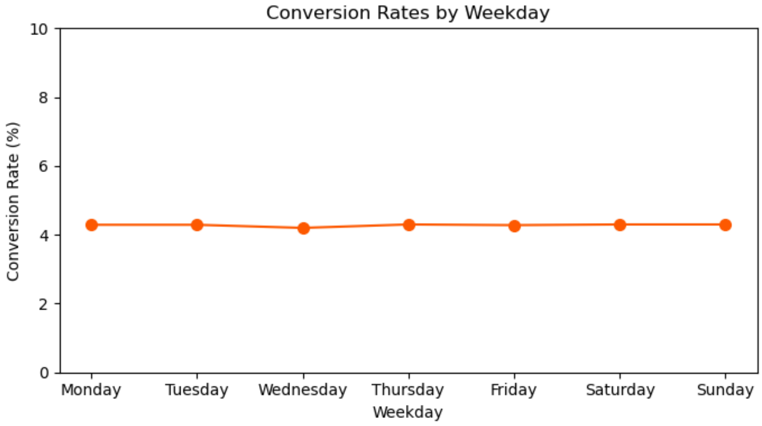

Figure 1: Conversion rates by weekdays.

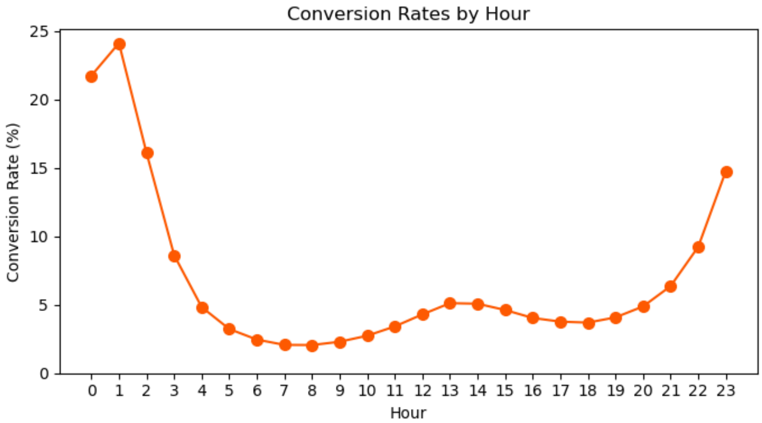

Figure 2: Conversion rates by hours.

While time-based conversion trends highlight opportunities to optimise banner displays, understanding user retention patterns provides deeper insights into customer behaviour. To this end, we turn to cohort analysis, which examines how user activity changes over time.

4 Cohort analysis

Cohort analysis is a powerful tool for tracking customer retention as it allows businesses to evaluate the effectiveness of their retention strategies and make data-driven decisions. By analysing the behaviour of specific customer groups (cohorts) over time, businesses can identify trends, compare retention rates, and pinpoint factors that impact customer loyalty, such as product updates or usage patterns. This approach provides actionable insights to improve long-term retention and predict key metrics like customer lifetime value and future revenue.

According to Peel Insights, a data analytics and consulting firm, the average annual retention rate for direct-to-consumer (DTC) e-commerce businesses is approximately 30%, with rates above 30% being considered exceptional[1]. However, the data from the monthly cohort analysis (fig. 3) indicates that this benchmark is not being achieved even in the first month,

[1]Repurchase vs. Retention Rate: How to measure and why these metrics are essential for DTC brands, available at peelinsights.com.

with retention rates between 14% and 17%. For readers interested in a more detailed view of user behaviour, please see the weekly cohort analysis in the Appendix.

These results highlight a suboptimal performance, suggesting that the business needs to focus on improving early-stage customer retention strategies. For example, improving the onboarding experience can help engage and retain new users during the critical first month. Offering incentives, such as discounts or exclusive perks, may encourage users to stay active and return for repeat visits. Additionally, it is essential to regularly monitor and analyse key behavioural metrics to identify and address areas requiring improvement. Beyond early retention, re-engaging inactive users through personalised email campaigns or app notifications can also prove effective. Loyalty programmes or gamified features could be introduced to sustain user interest and foster long-term engagement, ultimately boosting retention rates.

An additional kind of analysis that can be done on this data is the repurchase analysis, which examines how many customers from each cohort return to make additional purchases over time. This metric provides valuable insights into customer loyalty and the effectiveness of strategies aimed at encouraging repeat purchases.

Active Users

cohort start	month 0	month 1	month 2	month 3	month 4
Jan 1, 2019	721,429	101,786	44,788	35,091	28,171
Feb 1, 2019	532,143	87,993	28,988	21,902	
Mar 1, 2019	734,050	126,656	41,760		
Apr 1, 2019	828,082	140,897			
May 1, 2019	810,740				

Retention

cohort start	month 0	month 1	month 2	month 3	month 4
Jan 1, 2019	100.0	14.1	6.2	4.9	3.9
Feb 1, 2019	100.0	16.5	5.5	4.1	
Mar 1, 2019	100.0	17.3	5.7		
Apr 1, 2019	100.0	17.0			
May 1, 2019	100.0				

Figure 3: Monthly cohort analysis: active users and retention.

From the table in figure 4, we observe an overall declining pattern in repurchase rates after the first month, with less than 10% of customers returning by month 2 for most cohorts.

Repurchase Analysis by Monthly Cohort

cohort start	users	month 0	month 1	month 2	month 3	month 4
Jan 1, 2019	34,648	100.0	40.2	10.7	7.7	4.9
Feb 1, 2019	29,047	100.0	37.7	8.3	4.5	
Mar 1, 2019	38,816	100.0	38.3	8.1		
Apr 1, 2019	42,135	100.0	38.3			
May 1, 2019	28,355	100.0				

Figure 4: Monthly repurchase analysis by cohorts.

Based on industry benchmarks, this online shop is underperforming in terms of customer retention and repurchase rates. While the initial month 1 repurchase rates (around 38-40%)

align well with general expectations, they drop sharply in subsequent months, falling well below Alex Schultz's suggested healthy monthly range of 20-30%[2]. Compared to the apparel industry benchmark of a 12.6% 90-day repurchase rate for new customers[3], the shop's rates after month 3 (4-8%) are significantly lower. Furthermore, while the general e-commerce benchmark suggests 20-40% repurchase rates, the shop struggles to sustain this even in the short term, highlighting a need for stronger loyalty strategies and customer re-engagement efforts.

While the cohort and repurchase analyses provide a broad view of customer retention and loyalty, they do not reveal the detailed steps users take in their journey toward making a purchase. To compliment these findings, we now turn to funnel analysis, which tracks user actions from initial interaction to conversion. By analysing these stages, we can better understand where users disengage during their journey and identify opportunities to optimise the sales funnel.

5 Funnel analysis

In this report, the funnel analysis focuses on the first instances of each of these three stages for every individual customer:

1. Banner Show - the point at which a user views a banner on the website.
2. Banner Click - the user interacts with the banner by clicking on it.
3. Order - the final step where the user completes a purchase.

To gain deeper insights, we also analyse funnels for:

- Each month (5 months): to observe trends and seasonality in user behaviour.
- Each platform (2 platforms): to identify differences in performance across desktop and mobile platforms.
- Each product (4 categories): to assess how engagement and conversion vary by product type.

By identifying bottlenecks and underperforming areas, we aim to develop strategies to improve the overall user experience and drive higher conversion rates.

The general funnel analysis (fig. 5, table 2) provides an overview of user progression through three stages. From the data, the overall conversion rate (CVR) from banner display to purchase is 6.6%, significantly higher than the typical industry average for e-commerce, which ranges between 1.5% and 3%[4].

This elevated CVR is surprising, particularly in light of the findings from the cohort analysis (see previous section), which indicated high user drop-off rates and low repurchase rates over time. The discrepancy raises questions about the factors contributing to this result, such as potential influences of targeted marketing campaigns, promotional efforts, or the structure of the user journey.

[2] 12 Powerful Strategies to Increase Your Repeat Purchase Rate, available at theseventhsense.com.

[3] eCommerce Benchmarks - Do you know your 90 Day New Customer Repurchase Rate?, available at use-amp.com.

[4] The Average Website Conversion Rate by Industry (2024), available at invespcro.com.

Additionally, the high drop-off rates between stages (82.7% between Banner Show and Banner Click, and 61.7% between Banner Click and Order) suggest significant room for optimisation in engaging users and driving conversions at each step.

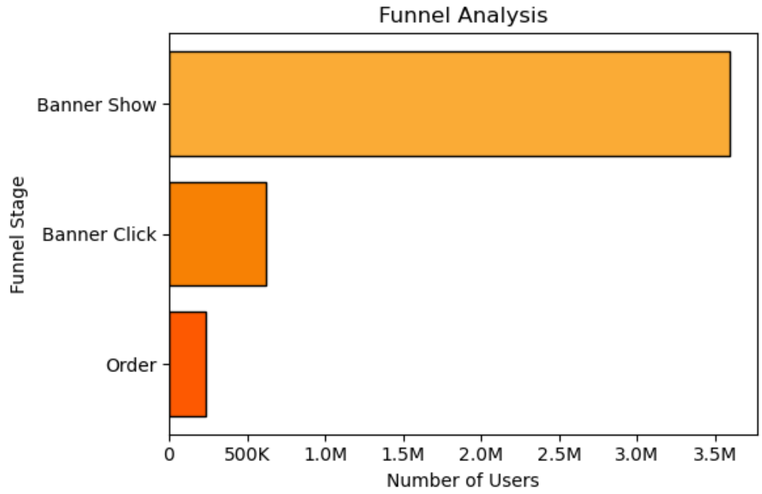

Figure 5: Overview of user progression through funnel stages.

Stage	Users	CVR (%)	Drop-Off (%)
Banner Show	3,592,738	100	0
Banner Click	620,508	17.3	82.7
Order	237,866	6.6	61.7

Table 2: Quantitative overview of funnel stages.

To investigate potential drivers of this high CVR, we conducted funnel analyses based on three different dimensions.

5.1 Monthly funnels

The monthly funnel analysis (fig. 6, table 3) reveals consistent performance across the months, with conversion rates (CVRs) ranging from 4% to 7%. February stands out as the best-performing month, achieving a CVR of 7%, although it had the lowest number of users entering the funnel.

Month	Banner Show			Banner Click			Order		
	Users	CVR	Drop-off	Users	CVR	Drop-off	Users	CVR	Drop-off
January	708,606	100	0	111,604	15.7	84.3	34,648	4.9	69.0
February	609,436	100	0	90,592	14.9	85.1	42,971	7.1	52.6
March	840,886	100	0	126,248	15.0	85.0	53,477	6.4	57.6
April	989,185	100	0	149,898	15.2	84.8	62,086	6.3	58.6
May	1,024,781	100	0	164,224	16.0	84.0	51,424	5.0	68.7

Table 3: Monthly funnel analysis showing the number of users, conversion rates (CVR), and drop-off rates for each stage of the funnel: Banner Show, Banner Click, and Order.

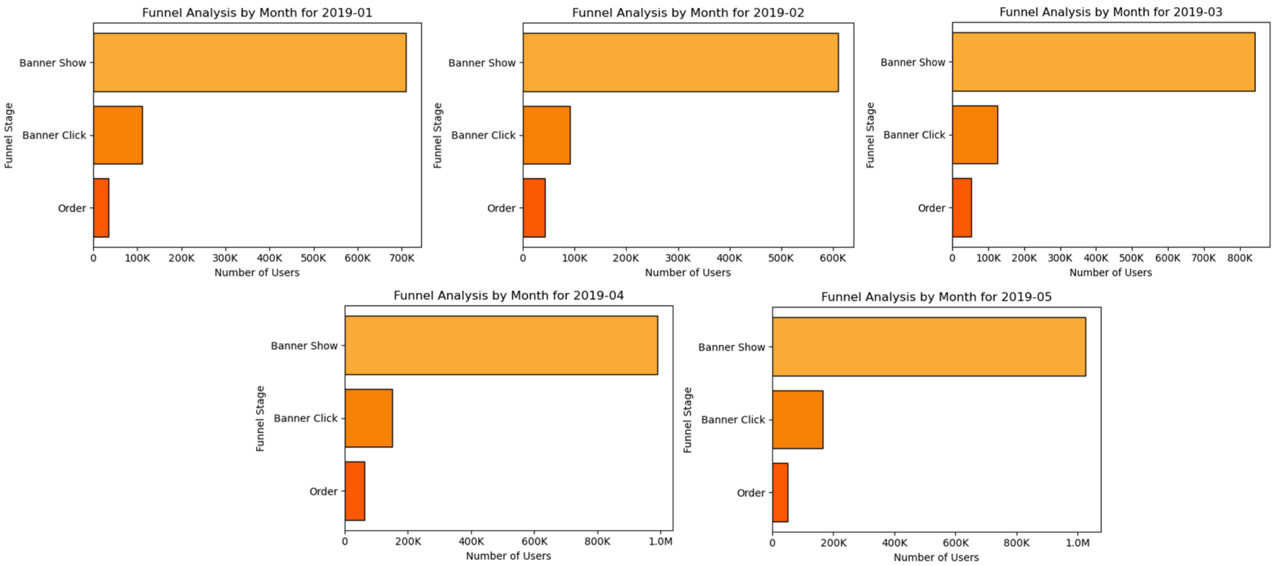

Figure 6: Funnel analysis by month. Left to right: January, February, March, April, May.

Across all months, the largest drop-off occurs between the Banner Show and Banner Click stages, with drop-off rates around 84-85%. This is a critical area for improvement, as most users fail to engage with the banner.

The drop-off between Banner Click and Order ranges from 52.6% to 69%, indicating some variability in user conversion after engaging with the banner. However, the overall CVRs remain relatively stable, showing no significant seasonal spikes or anomalies.

To improve conversion rates across all months, the business should focus on reducing drop-offs in the Banner Show to Banner Click stage by optimising banner designs, targeting, and calls-to-action. Additionally, analysing February's campaigns could provide insights to replicate successful strategies in other months.

5.2 Platform funnels

The platform-based funnel analysis (fig. 7, table 4) reveals significant differences in user behaviour and conversion rates between desktop and mobile users. Desktop users exhibit a conversion rate more than two times higher than mobile users. However, mobile platform exhibits significantly more banner shows (2,429,294 on mobile compared to 1,182,984 on desktop) and banner clicks (536,395 on mobile against 84,436 on desktop). At first glance, this discrepancy might suggest that users browse on mobile devices and later switch to desktop to complete their purchases. However, this theory is not supported by the data, as only about 20 thousand users out of 3.6 million use both platforms. The vast majority of users stick to their preferred platform, which means there must be other reasons for these differences.

Platform	**Banner Show**			**Banner Click**			**Order**		
	Users	**CVR**	**Drop-off**	**Users**	**CVR**	**Drop-off**	**Users**	**CVR**	**Drop-off**
Desktop	1,182,984	100	0	84,436	7.1	92.9	125,404	10.6	-48.5
Mobile	2,429,294	100	0	536,395	22.1	77.9	112,574	4.6	79.0

Table 4: Platform funnel analysis showing the number of users, conversion rates (CVR), and drop-off rates for each stage of the funnel: Banner Show, Banner Click, and Order.

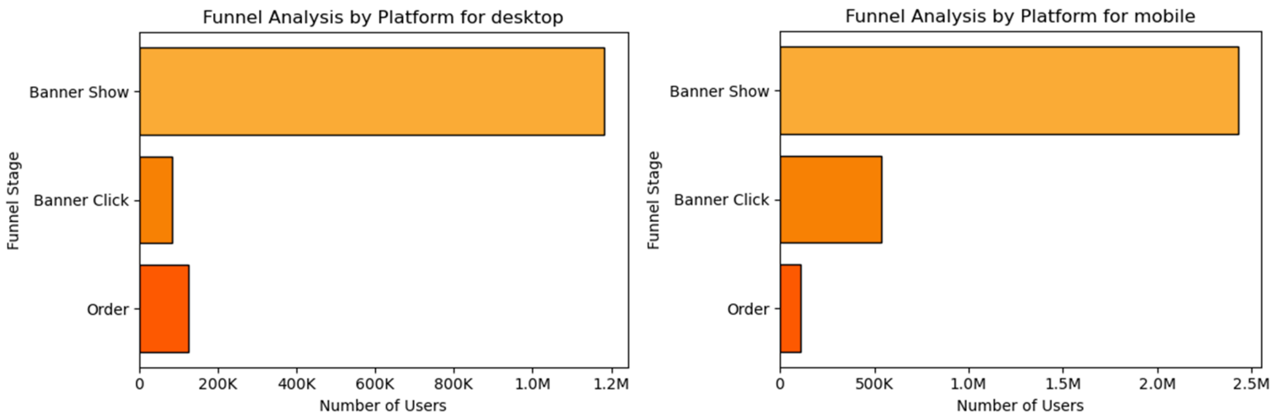

Figure 7: Funnel analysis by platform. Left to right: desktop, mobile.

One explanation is that mobile and desktop users have different intents when visiting the site. Mobile users may be more likely to browse and explore products without a strong intent to purchase, leading to higher engagement with banners but lower conversions. Desktop users, on the other hand, might visit the site with a clearer goal of making a purchase, resulting in fewer banner clicks but a higher overall conversion rate. These behavioural differences highlight the need for platform-specific strategies to optimise both user experiences and conversions.

The desktop funnel also shows an unusual pattern, with the number of orders exceeding the number of recorded banner clicks. This could be due to several factors. Desktop users might bypass banners entirely, arriving at the site through direct traffic, referrals, or other channels, and proceeding straight to purchase. Alternatively, the placement or design of banners on desktop may not be as effective at capturing user attention, leading to fewer clicks. Another possibility is that the attribution logic in the funnel does not fully account for alternative paths users take to complete their purchases, especially on desktop.

To address these challenges, several steps can be taken. For mobile, the focus should be on improving the shopping experience to encourage users to complete purchases directly on their phones. Simplifying the checkout process, optimising the website for mobile usability, and offering mobile-exclusive promotions could all help increase the mobile conversion rate. On desktop, a more effective banner strategy is needed to encourage users to engage with banners, which could include better placement, design, or messaging tailored to desktop browsing habits.

Additionally, further analysis of traffic sources is recommended to better understand how users arrive at the site on each platform. Breaking down traffic into direct, referral, search, and other categories can help clarify the paths users take to purchase and identify opportunities to optimise both mobile and desktop user journeys. These insights could help reduce the gap between banner engagement and conversions, leading to a more effective strategy for improving overall performance across platforms.

5.3 Product funnels

The product-level funnel analysis (fig. 8, table 5) reveals significant variations in conversion rates (CVR) across different categories. These differences suggest that some categories, particularly clothes, perform significantly better in converting users from banner views to purchases compared to others. This may be attributed to factors such as higher demand, better promotions, or more compelling banner designs for the clothes category.

Product	Banner Show			Banner Click			Order		
	Users	**CVR**	**Drop-off**	**Users**	**CVR**	**Drop-off**	**Users**	**CVR**	**Drop-off**
accessories	1,155,775	100	0	131,998	11.4	88.6	44,160	3.8	66.5
clothes	1,164,914	100	0	210,109	18.0	82.0	110,347	9.5	47.5
nutrition	1,173,163	100	0	139,854	11.9	88.1	23,609	2.0	83.1
sneakers	1,163,806	100	0	174,801	15.0	85.0	66,917	5.7	61.7

Table 5: Product funnel analysis showing the number of users, conversion rates (CVR), and drop-off rates for each stage of the funnel: Banner Show, Banner Click, and Order.

The clothes category stands out as an anomaly, achieving a CVR that is almost 2.5 times higher than that of accessories and over four times higher than sports nutrition. This could be logical, as clothes are likely a more frequent purchase for users compared to accessories or sports nutrition, but it also warrants further investigation to determine if specific strategies (e.g., better targeting or design) used for clothes can be replicated for other categories.

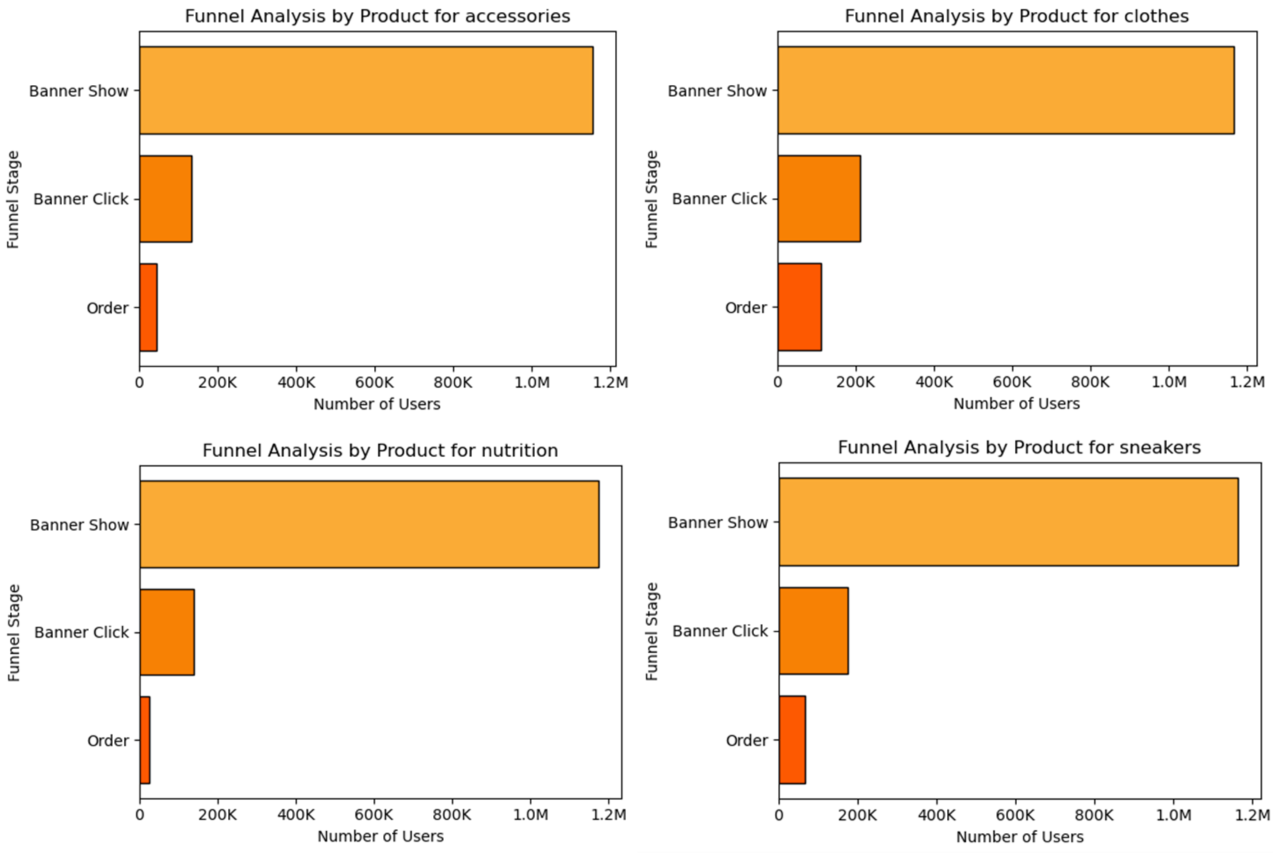

Figure 8: Funnel analysis by product. Left to right: accessories, clothes, nutrition, sneakers.

It may also be useful to revisit the current marketing strategies for accessories and sports nutrition. Approaches such as offering bundled discounts or using personalised recommendations could help improve their performance to match that of the higher-performing categories.

While the funnel analysis provides valuable insights into user behaviour and conversion rates across platforms and product categories, further statistical validation is needed to confirm whether the observed differences are significant. To address this, A/B testing is conducted on two key metrics: conversion rate (CVR) and click-through rate (CTR). These tests are performed across the same dimensions – overall performance, platform differences, and product categories.

Given the notable discrepancies between desktop and mobile performance observed in the funnel analysis, it will be particularly interesting to compare CVR and CTR between these platforms. Such comparisons can help us better understand how user behaviour differs across platforms and guide optimisation efforts to improve engagement and conversions.

6 A/B testing

To confirm the statistical significance of the differences observed in conversion rates (CVR) across platforms and products, we performed A/B testing comparing desktop and mobile users. These tests included a general comparison of desktop versus mobile performance, as well as comparisons for each product category (table 6).

The results of all the tests show a statistically significant difference in performance, leading to the rejection of the null hypothesis in every case. For CVR, desktop users consistently outperformed mobile users, with a higher likelihood of converting banner interactions into purchases. These results align with the findings from the funnel analysis, which showed that desktop users exhibit stronger purchase intent.

Conversely, the A/B tests on Click-Through Rates (CTR) reveal an opposite trend (table 6). Mobile users showed significantly higher engagement with banners across all product categories compared to desktop users, despite the lower conversion rates. This reinforces the hypothesis that mobile users are more likely to browse and explore, while desktop users are more focused on making purchases.

Test configuration	**CVR**			**CTR**		
	Z-stat	**P-value**	**Test result**	**Z-stat**	**P-value**	**Test result**
desktop vs. mobile	282.69	0.0	Reject H_0	-309.31	0.0	Reject H_0
desktop vs. mobile "accessories"	100.74	0.0	Reject H_0	-127.70	0.0	Reject H_0
desktop vs. mobile "clothes"	236.68	0.0	Reject H_0	-156.70	0.0	Reject H_0
desktop vs. mobile "nutrition"	68.96	0.0	Reject H_0	-168.06	0.0	Reject H_0
desktop vs. mobile "sneakers"	116.89	0.0	Reject H_0	-168.32	0.0	Reject H_0

Table 6: A/B test results comparing CVR and CTR for desktop and mobile users across different product categories. Positive Z-statistics indicate that the first category in a pair performs better, while negative Z-statistics indicate the opposite.

In addition, we conducted another set of A/B tests to analyse differences in CVR and CTR between product categories, independent of platform (table 7). The results highlight substantial variability in performance among categories. For CVR, "clothes" consistently outperform other product categories, achieving significantly higher conversion rates compared to "accessories," "nutrition," and "sneakers." On the other hand, "nutrition" and "accessories" show the lowest CVR, indicating underperformance in driving purchases relative to the other categories.

For CTR, the patterns indicate that user engagement with banners is relatively consistent across categories, with only minor variations. However, the weaker performance of categories like "accessories" and "nutrition" in terms of conversion suggests a gap between engagement and actual purchasing intent. This highlights an opportunity to improve banner strategies and targeting for these underperforming categories.

Test Configuration	CVR			CTR		
	Z-stat	**P-value**	**Test result**	**Z-stat**	**P-value**	**Test result**
"accessories" vs. "clothes"	-175.04	0.0	Reject H_0	-148.11	0.0	Reject H_0
"accessories" vs. "sneakers"	-69.10	0.0	Reject H_0	-84.51	0.0	Reject H_0
"accessories" vs. "nutrition"	82.88	0.0	Reject H_0	-12.39	0.0	Reject H_0
"clothes" vs. "sneakers"	109.36	0.0	Reject H_0	64.46	0.0	Reject H_0
"clothes" vs. "nutrition"	248.38	0.0	Reject H_0	136.68	0.0	Reject H_0
"sneakers" vs. "nutrition"	149.13	0.0	Reject H_0	72.57	0.0	Reject H_0

Table 7: A/B test results comparing CVR and CTR for every product pair. Positive Z-statistics indicate that the first category in a pair performs better, while negative Z-statistics indicate the opposite.

To visually summarise the differences observed in conversion rates (CVR) and click-through rates (CTR) between desktop and mobile users across product categories, we present the following bar charts (figures 9 and 10). These plots highlight the statistically proven trends revealed by the A/B tests.

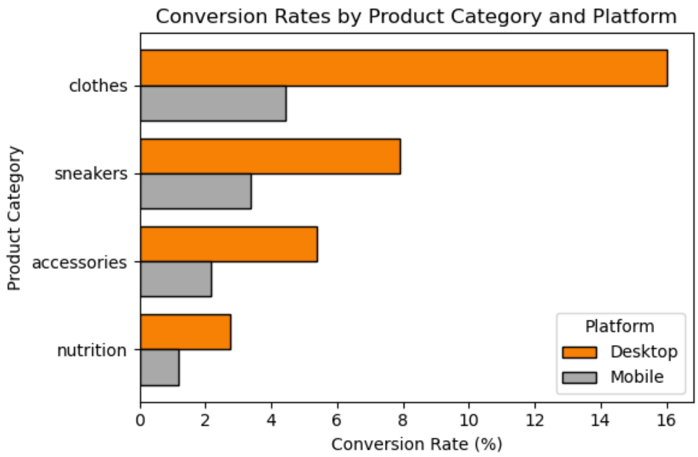

Figure 9: Conversion rates (CVR) by platform and product category.

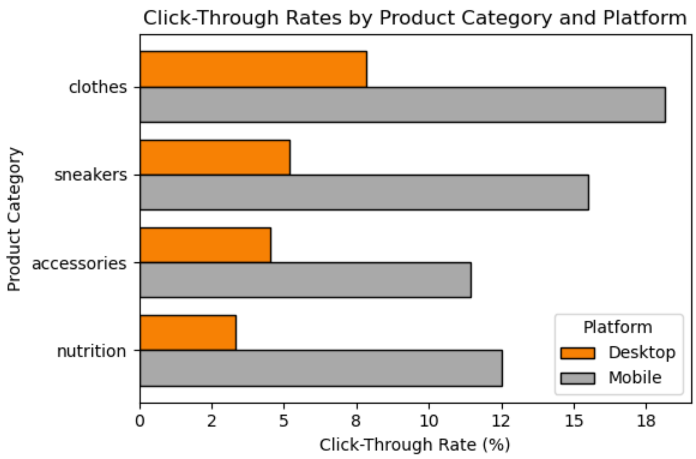

Figure 10: Click-through rates (CTR) by platform and product category.

Overall, the A/B testing confirms key behavioural patterns observed earlier in the analysis. Desktop users are more likely to convert, mobile users are more likely to engage, and "clothes" are the highest-performing category. These findings emphasise the need for platform-specific optimisation strategies and tailored marketing efforts for each product category to maximise both engagement and conversion rates.

7 Conclusion

This report provided a comprehensive analysis of user behaviour, retention, and conversion performance for the online sports store, using exploratory data analysis, cohort analysis, funnel analysis, and A/B testing. The findings reveal several patterns in user interactions, retention rates, and conversion behaviour, highlighting opportunities for optimisation and strategic improvements.

The analysis shows the disparity in performance between mobile and desktop users. Mobile users, despite accounting for the majority of interactions, exhibit significantly lower conversion rates compared to desktop users, who demonstrate stronger purchase intent. Among product categories, clothes consistently outperform others in driving conversions, achieving the highest conversion rates across both platforms. However, retention rates fall short of industry benchmarks, with repurchase rates dropping sharply after the first month, indicating challenges in fostering long-term customer loyalty.

To address these challenges, targeted strategies are recommended to optimise user engagement and improve conversion rates. These include simplifying the mobile shopping experience, enhancing desktop banner design, and replicating successful marketing strategies from high-performing categories to underperforming ones such as accessories and nutrition. Furthermore, focusing on early retention through improved onboarding and targeted incentives can mitigate drop-offs, while refining banner timing and analysing traffic sources will help maximise overall performance.

By implementing these recommendations, the business can enhance user retention, drive higher conversions, and achieve a more effective marketing strategy that aligns with the behavioural patterns identified in this report.

Appendix

cohort_start	week 0	week 1	week 2	week 3	week 4	week 5	week 6	week 7	week 8	week 9	week 10	week 11	week 12	week 13	week 14	week 15	week 16	week 17	week 18	week 19	week 20	week 21
Dec 31, 2018	179,795	51,925	31,955	15,048	10,126	7,209	6,005	5,139	4,642	4,140	3,895	3,768	3,601	3,458	3,217	3,191	3,114	3,005	2,905	2,805	2,417	1,243
Jan 7, 2019	222,654	42,282	28,293	14,457	10,272	7,498	6,220	5,420	5,111	4,707	4,722	4,513	4,303	4,067	3,929	3,859	3,674	3,572	3,551	2,862	1,541	
Jan 14, 2019	189,265	34,277	22,827	11,562	8,017	5,645	4,764	4,305	4,029	3,983	3,804	3,690	3,325	3,243	3,148	3,064	2,956	2,890	2,433	1,297		
Jan 21, 2019	174,908	31,148	21,303	10,534	6,926	4,795	4,136	3,712	3,602	3,437	3,275	2,931	2,984	2,946	2,853	2,827	2,535	2,294	1,179			
Jan 28, 2019	169,088	30,860	21,083	9,715	6,412	4,492	3,825	3,651	3,539	3,352	3,132	2,983	2,797	2,732	2,717	2,641	2,220	1,135				
Feb 4, 2019	165,138	28,658	19,324	9,472	6,096	4,254	3,870	3,442	3,194	2,979	2,870	2,695	2,707	2,499	2,400	2,061	1,071					
Feb 11, 2019	164,173	28,951	20,139	9,451	6,240	4,521	3,759	3,467	3,023	2,999	2,826	2,833	2,604	2,618	2,158	1,113						
Feb 18, 2019	164,129	29,266	19,990	9,397	6,455	4,471	3,846	3,362	3,143	2,917	2,803	2,651	2,525	2,228	1,132							
Feb 25, 2019	165,928	29,387	20,146	9,943	6,523	4,566	3,778	3,400	3,262	3,038	2,856	2,781	2,312	1,172								
Mar 4, 2019	174,507	31,818	22,787	10,731	7,195	4,746	4,216	3,612	3,518	3,248	3,132	2,674	1,363									
Mar 11, 2019	181,825	34,008	23,720	11,473	7,419	5,239	4,409	4,098	3,704	3,480	3,015	1,439										
Mar 18, 2019	207,144	40,616	30,204	13,278	8,677	6,297	5,514	4,999	4,681	4,034	2,040											
Mar 25, 2019	212,962	41,832	27,471	13,514	9,084	6,723	5,957	5,464	4,549	2,384												
Apr 1, 2019	219,525	40,752	28,389	13,675	9,600	7,012	6,337	4,975	2,545													
Apr 8, 2019	214,512	40,275	28,059	13,987	9,411	6,954	5,467	2,605														
Apr 15, 2019	223,148	42,350	30,354	14,289	10,135	6,725	3,184															
Apr 22, 2019	227,985	43,963	30,498	14,975	9,716	4,002																
Apr 29, 2019	238,459	46,564	33,393	15,366	6,268																	
May 6, 2019	238,336	48,405	32,814	10,654																		
May 13, 2019	242,659	49,881	26,721																			
May 20, 2019	197,791	28,719																				
May 27, 2019	80,688																					
average	198,759	37,902	25,974	12,185	8,032	5,597	4,705	4,110	3,753	3,438	3,198	2,996	2,852	2,774	2,694	2,679	2,595	2,579	2,517	2,321	1,979	1,243

Figure 1: Active users by weekly cohort, with conditional formatting applied independently to each column.

cohort_start	week 0	week 1	week 2	week 3	week 4	week 5	week 6	week 7	week 8	week 9	week 10	week 11	week 12	week 13	week 14	week 15	week 16	week 17	week 18	week 19	week 20	week 21
Dec 31, 2018	100.0	28.9	17.8	8.4	5.6	4.0	3.3	2.9	2.6	2.3	2.2	2.1	2.0	1.9	1.8	1.8	1.7	1.7	1.6	1.6	1.3	0.7
Jan 7, 2019	100.0	19.0	12.7	6.5	4.6	3.4	2.8	2.4	2.3	2.1	2.1	2.0	1.9	1.8	1.8	1.7	1.7	1.6	1.6	1.3	0.7	
Jan 14, 2019	100.0	18.1	12.1	6.1	4.2	3.0	2.5	2.3	2.1	2.1	2.0	1.9	1.8	1.7	1.7	1.6	1.6	1.5	1.3	0.7		
Jan 21, 2019	100.0	17.8	12.2	6.0	4.0	2.7	2.4	2.1	2.1	2.0	1.9	1.7	1.7	1.7	1.6	1.6	1.4	1.3	0.7			
Jan 28, 2019	100.0	18.3	12.5	5.7	3.8	2.7	2.3	2.2	2.1	2.0	1.9	1.8	1.7	1.6	1.6	1.6	1.3	0.7				
Feb 4, 2019	100.0	17.4	11.7	5.7	3.7	2.6	2.3	2.1	1.9	1.8	1.7	1.6	1.6	1.5	1.5	1.2	0.6					
Feb 11, 2019	100.0	17.6	12.3	5.8	3.8	2.8	2.3	2.1	1.8	1.8	1.7	1.7	1.6	1.6	1.3	0.7						
Feb 18, 2019	100.0	17.8	12.2	5.7	3.9	2.7	2.3	2.0	1.9	1.8	1.7	1.6	1.5	1.4	0.7							
Feb 25, 2019	100.0	17.7	12.1	6.0	3.9	2.8	2.3	2.0	2.0	1.8	1.7	1.7	1.4	0.7								
Mar 4, 2019	100.0	18.2	13.1	6.1	4.1	2.7	2.4	2.1	2.0	1.9	1.8	1.5	0.8									
Mar 11, 2019	100.0	18.7	13.0	6.3	4.1	2.9	2.4	2.3	2.0	1.9	1.7	0.8										
Mar 18, 2019	100.0	19.6	14.6	6.4	4.2	3.0	2.7	2.4	2.3	1.9	1.0											
Mar 25, 2019	100.0	19.6	12.9	6.3	4.3	3.2	2.8	2.6	2.1	1.1												
Apr 1, 2019	100.0	18.6	12.9	6.2	4.4	3.2	2.9	2.3	1.2													
Apr 8, 2019	100.0	18.8	13.1	6.5	4.4	3.2	2.5	1.2														
Apr 15, 2019	100.0	19.0	13.6	6.4	4.5	3.0	1.4															
Apr 22, 2019	100.0	19.3	13.4	6.6	4.3	1.8																
Apr 29, 2019	100.0	19.5	14.0	6.4	2.6																	
May 6, 2019	100.0	20.3	13.8	4.5																		
May 13, 2019	100.0	20.6	11.0																			
May 20, 2019	100.0	14.5																				
May 27, 2019	100.0																					
average	100.0	19.0	13.0	6.2	4.1	2.9	2.5	2.2	2.0	1.9	1.8	1.7	1.6	1.5	1.5	1.5	1.4	1.4	1.3	1.2	1.0	0.7

Figure 2: Retention rate (%) by weekly cohort, with conditional formatting applied independently to each column.