Teesside University International Business School

Digital Optimisation Opportunities, Analytics & Metrics, Micro and Macro Conversion Assessments

Prepared by

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Word count: 2850

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ACKNOWLEDGEMENT

The report is analysed and written using academic literature, marketing models, frameworks, and class materials provided throughout the module. It also incorporates the available data sets from TUIBS LinkedIn Page to simulate the analysis and demonstrate understanding of digital marketing analytics.

INTRODUCTION

Teesside University International Business School (referred to as TUIBS) is a forward-thinking, industry-focused institution based in the main campus in Teesside, Middlesbrough. It is known for having strong industry links and providing a blend of practical and theory learnings.

Institutions such as TUIBS face the challenge of increasingly greater competition in higher education, particularly attracting both domestic and international undergraduate and post-graduate students. It faces the challenge of adapting to the ever-changing digital landscape to attract students using a data-driven approach and digital marketing strategies to increase visibility, raise interest, and influence conversions.

This report analyses key analytical models to identify the workable metrics across acquisition, behaviours, and conversion phases. Understanding the metrics and using relevant data for analytics, finding touchpoints, mapping customer journey, and continuous improvement is the key to digital optimisation and enabling organisations to make informed decisions throughout the customer journey (Chaffey, 2023). The report further demonstrates how TUIBS can measure the return on investment (ROI) from its digital marketing efforts to improve conversions.

COMPARING DIFFERENT ANALYTICAL MODELS

The analysis to determine the performance of TUIBS digital marketing approach across each platform is done by comparing three models, which are Attribution modelling, Markov Chain modelling, and Marketing Mix modelling. Below are the details of the efficiency of each model, comparing their strengths and weaknesses.

ATTRIBUTION MODELLING

Attribution modelling is assigning values to each of its customer journey touchpoints and analysing the values to determine the scale of attention needed across each touchpoint that contributes to maximum conversions. The first-click attribution, which puts the most importance on the initial awareness, is inefficient for understanding the marketing flaws beyond the initial interaction that may impede the journey flow. Last-click attribution, although as easy as the first-click attribution to implement, ignores the earlier influences (Li and Kannan, 2014) and credits the final interaction disproportionately. Time-decay and Linear attribution models, where the touchpoint credits increase over time or remain constant, respectively, are too simplified and fail to recognise the paths that are yielding more results across the journey. Data-driven model is the best digital marketing approach for TUIBS, but it requires sophisticated analytics, continuous tracking, and larger data sets, requiring a greater resource allocation and a larger qualified marketing team. View figures 1 and 2, where the data-driven attribution model is demonstrated using Google Analytics 4 (GA4), indicating the changing scale of contribution of touchpoints across the customer journey.

Therefore, these attribution models alone are insufficient to capture the complexity in higher education journeys where decision-making is a longer cycle and involves multiple interactions involving multi-channel journeys.

MARKOV CHAIN MODELLING

Markov Chain modelling is a form of attribution modelling which uses a probabilistic and calculative approach, emphasizing the probability of transitions between each touchpoint in the customer journey leading to conversions or exit (Anderl et al., 2016).

Compared to the aforementioned attribution models, the Markov Chain model offers a rule-based approach to capture the complexity of the entire customer journey into a chain of probable journeys rather than relying on arbitrary assumptions (Kanna, 2022). For TUIBS, applying this model would allow a scientifically rigorous analysis of the multi-channel effectiveness by using the Removal Effect and quantifying the impact of eliminating certain touchpoints (TripleWhale, 2026). Moreover, compared to Data-Driven Attribution which is a complex machine learning analysis, Markov Chains are less intensive and use smaller datasets more effectively, making them more practical for campaign-level analysis (Adequate Digital, 2026; Corvidae AI, 2021).

View Table 1, which demonstrates a simulated Markov Chain Model based on online sources and established literature, funnel theories, customer journey research, and industry benchmarks, as individual-level journey data is unavailable. They are stated as follows:

- Users have a higher probability of moving from social to website to conversion (Chaffey, 2023).
- Students are likely to search over search engines and do multiple searches (Lemon & Verhoef, 2016).
- LinkedIn is efficient for awareness and consideration, but has lower conversion probabilities compared to the website. (Halligan & Shah, 2014); LinkedIn Marketing Reports
- Email has a high conversion probability (Campaign Monitor,2023)

Table 1: Simulated Markov Chain modelling for TUIBS

From \ To	**LinkedIn**	**Google**	**Website**	**Email**	**Other Social**	**Open Day**	**Prospectus**	**Enquiry**	**Exit**
LinkedIn	0%	12%	45%	10%	10%	10%	8%	3%	2%
Google Search	5%	0%	50%	10%	5%	10%	10%	5%	5%
Website Direct	5%	5%	0%	20%	5%	25%	20%	15%	5%
Email	2%	3%	35%	0%	2%	25%	20%	10%	3%
Other Social	25%	10%	35%	5%	0%	10%	5%	5%	5%

The probabilities are calculated using the formula:

Equation 1: Probability calculation for Markov Chain Modelling

$$P = \frac{Users\, who\ left\ from\, platform}{Total\ users\ at\ the\ platform}$$

Using Table 2, we can calculate the probability of LinkedIn users inquiring about open day, prospectus, and applying, using no or one intermediary path.

Table 2: Probability of conversions from TUIBS LinkedIn page as the first touchpoint

LinkedIn to Goal	**Via Google**	**Via Website**	**Via Email**	**Via Other Social**

(10%+8%+3%) = 21%	12%*(10%+10%+5%) = 3%	45%*(25%+20%+15%) = 27%	10%*(25%+20%+10%) = 5.5%	10%*(10%+5%+5%) = 2%

Total conversion probability from LinkedIn = 21%+3%+27%+5.5%+2% = 58.5%

The removal effect of LinkedIn in the funnel is very apparent, which significantly reduces traffic entering the system. It is not only a key discovery tool for TUIBS but also an important contributor to the funnel. View Table 3, which displays the removal effect of different channels on TUIBS digital marketing effort.

Equation 2: Removal Effect calculation

$$Removal\ Effect = \frac{Total\ Conversion\ Probability\ from\ a\ platform - Total\ Conversion\ Probability\ without\ the\ platform}{Total\ Conversion\ Probability\ from\ a\ platform} \times 100\%$$

Assuming the adjusted conversion probability without LinkedIn is 40%, the removal effect is calculated as follows

Removal Effect = 58.5%-40%/58.5% *100 = 31.6% decrease

Table 3: Removal Effect of different channels in the TUIBS digital funnel

Channel Removed	**Conversion Drop**
LinkedIn	~30-35%
Website	~35-40%
Email	~15-20%

Hence it can be interpreted that LinkedIn acts as a top funnel driver, whereas the website is the main conversion hub, and email is the conversion accelerator.

MARKETING MIX MODELLING (MMM)

The Marketing Mix Modelling uses an aggregated mix of factors impacting the marketing efforts. It is in the analysis of the marketing inputs alongside external variables such as economic conditions and seasonal impacts (Chaffey, 2023). It is suitable for long-term strategic planning rather than immediate impacts, unlike the Attribution Model and the Markov Chain Model. Therefore, it lacks granular level analysis, making it unsuitable to track customer journeys, ultimately limiting the ability to optimise real-time specific touchpoints.

COMPARISON AND RECOMMENDATION

Comparing all three models, it can be determined that each has its own set of strengths and weaknesses. A summary is done in Table 4.

Table 4: Strengths and limitations of the analytical models

Model	Strengths	Limitations
Attribution	Simple, actionable	Oversimplifies journeys
Markov	Accurate, data-driven	Complex, data-intensive
MMM	Strategic insights	No user-level data

Based on this analysis, a hybrid approach is recommended for TUIBS. For campaign-level optimisation, a data-driven attribution model can provide effective insights, while Markov Chain modelling allows understanding of touchpoint contributions across the customer journeys. MMM can guide a long-term solution to external factors and budget allocation. This multi-model approach allows the best practice in digital analytics, where combining the strengths of each in turn overcomes the individual limitations (Chaffey, 2023).

ACQUISITION METRICS

The process of attracting potential students to enquire about courses in TUIBS through the digital platforms used is Acquisitions for TUIBS. It is a critical part of the funnel indicating the performance of the awareness efforts (Kotler et al., 2019).

KEY METRICS

The metrics determined collectively provide a comprehensive view of the top-of-funnel performance.

TUIBS should track the following acquisition metrics:

- Reach, Impressions, and Website traffic: Evaluates visibility of TUIBS. Figure 3 demonstrates user count and percentages for the website along with average engagement rates, indicating how each channel is contributing to the overall acquisition.
- Click-through rate (CTR) and Cost per click (CPC): Assesses the relevancy and cost effectiveness. Figure 4 shows how CPC and CTR are calculated using the clicks and

impression metrics in Google Ads, where decreasing CPC indicates a better performance. Figure 17 also shows the CPC tracking using GA4.

- Follower growth: Indicates returning potential and future engagement. Figure 5 illustrates a decrease in post frequency impacts the page views, disrupting top-of-the-funnel entries for TUIBS LinkedIn page. Figure 6 displays their follower growth over time, indicating that a decrease in posting frequency leads to a reduction in the rate of follower growth.

Integrating all these metrics would enable TUIBS to have a data-driven approach during the acquisition stage by turning raw data into actionable insights (Chaffey, 2023).

DATASET INSIGHTS AND IMPROVEMENT STRATEGIES

The competitor analysis shows that the University of Sunderland and Durham University Business School significantly outperform TUIBS in engagement and reach. Figure 7 demonstrates the discrepancies of follower count and post engagements.

To increase acquisition, TUIBS should:

- Invest in LinkedIn as a primary channel for PG recruitment
- Use video content to increase engagement (91% of marketers see video as effective (Wyzowl, 2023))
- Engage in SEO for course-related search queries
- Apply personalisation and audience segmentation

BEHAVIOUR METRICS

The interaction after initial acquisition for TUIBS is generalised as the behaviour of traffic. Behaviour metrics are crucial to understanding the engagement via effective communication strategies, keeping the users in their journey loop, corresponding to the consideration (Lemon and Verhoef, 2016).

Going beyond passive engagement, such as likes and reactions, meaningful interactions are crucial for TUIBS digital marketing efforts for understanding genuine interest. Examples include:

- Comments and shares
- Brochure downloads
- Webinar registrations

Such actions give clarity of users' progression towards conversion.

KEY BEHAVIOUR METRICS

Key indicators of meaningful interactions, engagement quality, and intent are stated below which are recognised as effective metrics in digital analytics during the consideration stage (Lemon and Verhoef, 2016).

- Time on site: Indicates the depth of user engagement, where longer duration is proportional to higher interest and probability for conversion (Chaffey, 2023). Figure 8 shows the average engagement time for each active user on the website.
- Bounce rate: Indicates content relevance, where a higher bounce rate reflects a mismatch between user expectations and content delivery (Google, 2023).
- Pages per session: Indicates navigation interest, specifically important in measuring high-stakes decision making such as university selection (Kotler et al., 2019). Figure 9 shows pages viewed per session from traffic coming across various channels.
- Engagement rate: Signals audience interaction and content effectiveness on social platforms. Figures 10 and 11 illustrate the behaviour of TUIBS LinkedIn page visitors regarding their interaction with content type, demonstrating that certain types of content, such as thought leadership, brand authority, and humanized community content, generate higher engagement than others.
- Video completion rate: Indicates user attention for TUIBS, adding to significantly improve recollection and decision-making (Wyzowl, 2023).

BEHAVIOUR GOALS

Classified as micro-conversions, the following goals act as a contributing factor to the final conversions (Chaffey, 2023).

- Prospectus downloads: Indicates intent for learning about the courses offered, which are often a step towards the final decision-making for application submissions in higher education (Lemon and Verhoef, 2016).
- Open day bookings: Reflect commitment as they require time investment and learning intent for the institution.
- Video engagement: Shows emotional connection and persuasion crucial in the decision-making processes (Kotler et al., 2019).

Tracking these micro-conversions for TUIBS improves prediction and signals interaction through the decision-making funnel towards application inquiry (Anderl et al., 2016).

CONVERSION METRICS

A conversion is defined when a user completes a desired action, such as submitting an application (Chaffey, 2023). It is the end of the funnel phase where the metrics evaluate how effective the digital marketing efforts are working by turning prospective students into applicants and enrols for TUIBS, directly connected to measuring the return on investment.

TYPES OF CONVERSIONS

Reflecting the progression optimisation effectiveness through the marketing funnel, it is crucial to distinguish between micro (short-term) and macro (long-term) conversions and apply strategies accordingly, as supported in digital marketing literature (Chaffey, 2023).

SHORT-TERM (MICRO CONVERSIONS):

Micro conversion recognizes early intent, helping on the final push towards conversions (Anderl et al., 2016). The following metrics are identified as micro conversions.

- Newsletter sign-ups: Indicates interest to stay in contact with TUIBS, reflecting early interests and opportunity to further optimise messages over time through email marketing (Chaffey, 2023).
- Form submissions: Indicates active enquiries and stronger intent compared to passive engagement (Lemon and Verhoef, 2016).
- Open day bookings: Represent a significant commitment, increasing the likelihood of applications.

LONG-TERM (MACRO CONVERSIONS):

Macro conversions are the ultimate business outcomes that are directly linked to organisational objectives such as student recruitment (Kotler et al., 2019). It is often the combination of multiple micro-conversions across the customer journey (Lemon and Verhoef, 2016) and institutions that track and optimise both micro and macro conversions achieve higher overall conversions (Chaffey, 2023).

- Course applications: The primary measurable goal of successful marketing efforts in higher education.
- Enrolments: It is the final conversion and directly contributes to revenue.

KEY METRICS

The selected conversion metrics are essential for evaluating TUIBS's recruitment funnel.

- Conversion rate: Measures how effectively traffic is turned into desired outcomes (e.g., applications or enquiries). Figure 12 demonstrates how both session and user conversion rate can be tracked using GA4 across multiple stages and conversion points in the user journey.
- Cost per acquisition (CPA): Reflects the cost of marketing activities to acquire a lead, where an increase in conversion can reduce acquisition costs and improve ROI. Figure 17 displays an example of CPA calculation using GA4.
- Lead-to-enrolment ratio: Relevant to higher education, it shows how the digital marketing efforts within multiple touchpoints are contributing to final outcomes (Lemon and Verhoef, 2016).

Together, these metrics ensure that conversion for TUIBS is evaluated not only by volume but also by quality and cost reduction.

Equation 3: CPA calculation

$$CPA = \frac{Cost}{Conversions}$$

Equation 4: Conversion Rate calculation

$$Conversion\ Rate = \frac{Conversions}{Total\ Visitors} \times 100\%$$

PLATFORM-SPECIFIC TRACKING

Due to the multi-interaction nature of the customers, tracking both the website and social media is crucial for TUIBS.

- Website: applications, downloads, session behaviour
- Social media: clicks, leads generated, engagement-to-conversion ratio

Website yield the high intent actions by students, whereas social media acts as an effective awareness and engagement tool. Hence, the performance should be measured as a collective rather than in isolation.

CONTENT ROI MEASUREMENT

ROI is the measure of the effectiveness of the marketing investments, ensuring the resources are allocated and converted into outcomes efficiently. An absence of thorough ROI analysis without evidence-led effort can lead to TUIBS risking investment decisions.

Equation 5: ROI calculation

$$ROI = \frac{Revenue - Cost}{Cost}$$

TRACKING CONTENT PERFORMANCE

Tracking the following allows TUIBS to have a holistic approach throughout the progression of awareness, interaction, and conversion funnel. Tools such as Google Analytics 4 can be used to link content performance to user actions.

- Reach: Measures content visibility essential for evaluating awareness (Kotler et al., 2019). Figures 13 and 14 show the performance across countries and channels, including the first user.
- Engagement: Reflects how audiences interact with interest and relationship building (Tuten and Solomon, 2020). Figures 15 and 16 display how users are contributing to events within the website. Such metrics indicate not only awareness success but also how they are behaving.
- Conversion: Measures meaningful outcomes, being the direct indicator of effectiveness and ROI (Chaffey, 2023). Figure 17 presents a GA4 tracking of conversion performance, including the ad cost, total revenue, and ROAS.

LINKING CONTENT TO ACTION

To accurately measure the multi-touch nature of the funnel, TUIBS should adopt tracking and attribution techniques and assess whether the content is driving the desired user actions.

- UTM parameters and tracking links: Tags that enable precise tracking of traffic sources, allowing a thorough investigation of what content pieces and behaviors lead to user actions (Google, 2023). Figure 18 gives an example of UTM parameters and tags added in the HTML header of websites.
- Attribution and Markov models: A distribution of credits and probabilistic interactions provides a more in-depth understanding of how different touchpoints contribute to conversions, overcoming the limitations of single-touch attribution models (Anderl et al., 2016).

- Funnel analysis: Allows identifying where users drop off or proceed, indicating optimisation and calls-to-action effectiveness across different stages (Lemon and Verhoef, 2016). Figures 19 and 20 show how the user journey can be tracked and analysed while taking the abandoned rate into consideration to minimize drop-off points.

For example, if LinkedIn posts generate high engagement but low conversions, this suggests a disconnect between content and call-to-action.

CONCLUSION

This report demonstrates that a combination of analytical models supported with correct metrics and a strategic process enables a strong digital optimisation approach for TUIBS. While Data-Driven Attribution model is programmatic machine learning, Markov Chain is simpler in comparison, requiring fewer sample data and being effective in understanding the removal effects of channels and their interdependencies. The other attribution models are too simplified for TUIBS, whereas Markov Chain is a scientific, calculative, and logical modelling enabling a much more rigorous insight into channel contributions. Ultimately, Attribution, Markov Chain, and Marketing Mix Modelling each offer unique strengths, a hybrid of which enables a stronger digital marketing process.

By focusing on acquisition, behaviour, and conversion metrics using the proper data sets that clearly show results, TUIBS can improve its approach to audience messaging and improve recruitment outcomes. Using the platform-specific tracking and analytics, such as LinkedIn analytics, Meta, and YouTube Studio, important metrics can be tracked and evaluated. A shift to value-driven, authentic posting, especially on the LinkedIn page, would increase the viewer reach, engagement, and increase conversion probabilities. GA4 provides a strong platform to analyse and optimise the TUIBS website. TUIBS can leverage their website as a conversion hub by improving the navigation for a smoother path to their behaviour goals, as well as their micro and macro conversions, such as open day booking, prospectus downloads, form submissions, and applications. The lead-to-enroll rate is a strong indicator of the impact of digital marketing efforts that TUIBS can use to evaluate success. Moreover, a thorough measurement of content ROI with proper Revenue and Cost tracking ensures that digital marketing efforts are aligned with TUIBS' goals.

Ultimately, to remain competitive in an increasingly digitalized and data-driven landscape by higher education institutions, TUIBS' key to success lies in effectively tracking and transforming data into actionable insights.

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APPENDICES

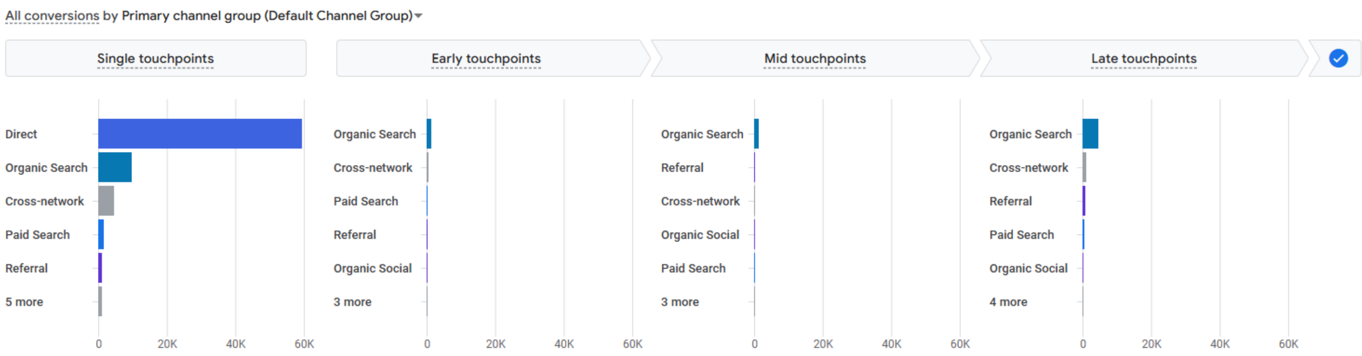


Figure 1: Comparisons of total data driven attribution across different touchpoints in the user journey

Search... Rows per page: 250 1-10 of 10

		Attribution model (non-direct) Last click Paid and organic channels		Attribution model (non-direct) Data-driven Paid and organic channels		% Change	
	Primary channel...Channel Group)	All conversions	Total revenue (by int. time)	All conversions	Total revenue (by int. time)	All conversions	Total revenue
	Total	89,961.00 100% of total	$148,585.59 100% of total	89,312.97 100% of total	$145,644.63 100% of total	-0.72%	-1.98%
1	Direct	59,362.00 (65.99%)	$93,298.92 (62.79%)	59,362.00 (66.47%)	$93,298.92 (64.06%)	0%	0%
2	Organic Search	18,056.00 (20.07%)	$34,369.80 (23.13%)	16,825.19 (18.84%)	$32,269.06 (22.16%)	-6.82%	-6.11%
3	Cross-network	5,538.00 (6.16%)	$4,443.08 (2.99%)	6,190.44 (6.93%)	$4,880.34 (3.35%)	11.78%	9.84%
4	Paid Search	2,522.00 (2.8%)	$7,684.68 (5.17%)	2,637.97 (2.95%)	$6,566.80 (4.51%)	4.6%	-14.55%
5	Referral	2,325.00 (2.58%)	$5,765.87 (3.88%)	2,236.52 (2.5%)	$5,734.36 (3.94%)	-3.81%	-0.55%
6	Organic Social	838.00 (0.93%)	$1,357.86 (0.91%)	807.16 (0.9%)	$1,357.86 (0.93%)	-3.68%	0%
7	Unassigned	631.00 (0.7%)	$695.62 (0.47%)	575.76 (0.64%)	$426.81 (0.29%)	-8.75%	-38.64%
8	Organic Shopping	567.00 (0.63%)	$712.37 (0.48%)	557.73 (0.62%)	$853.08 (0.59%)	-1.63%	19.75%
9	Organic Video	81.00 (0.09%)	$122.16 (0.08%)	79.91 (0.09%)	$122.16 (0.08%)	-1.34%	0%
10	Email	41.00 (0.05%)	$135.23 (0.09%)	40.28 (0.05%)	$135.23 (0.09%)	-1.74%	0%

Figure 2: Comparing data-driven with last click attribution model using GA4

	First user prim…Channel Group)	Total users	↓ New users	Returning users	Average online active user engagement time	Engaged online sessions per active user	Event count All events	Key events All events	User key event rate All events
	Total	21,523 100% of total	16,004 100% of total	3,116 100% of total	42s Avg 0%	0.35 Avg 0%	232,032 100% of total	14,803.00 100% of total	16.65% Avg 0%
1	Direct	16,422 (76.3%)	12,452 (77.81%)	1,902 (61.04%)	31s	0.22	141,368 (60.93%)	8,350.00 (56.41%)	10.22%
2	Organic Search	2,253 (10.47%)	1,683 (10.52%)	538 (17.27%)	1m 13s	0.90	38,219 (16.47%)	2,497.00 (16.87%)	42%
3	Cross-network	1,242 (5.77%)	897 (5.6%)	305 (9.79%)	2m 01s	1.03	30,372 (13.09%)	2,499.00 (16.88%)	50.88%
4	Unassigned	718 (3.34%)	499 (3.12%)	44 (1.41%)	25s	0.14	4,518 (1.95%)	98.00 (0.66%)	5.52%
5	Paid Search	381 (1.77%)	285 (1.78%)	96 (3.08%)	1m 25s	0.82	6,217 (2.68%)	343.00 (2.32%)	34.64%
6	Referral	388 (1.8%)	84 (0.52%)	158 (5.07%)	1m 45s	1.00	6,389 (2.75%)	476.00 (3.22%)	43.61%
7	Organic Social	97 (0.45%)	54 (0.34%)	21 (0.67%)	1m 27s	0.90	1,949 (0.84%)	214.00 (1.45%)	52.11%
8	Organic Shopping	54 (0.25%)	41 (0.26%)	9 (0.29%)	1m 51s	1.12	1,208 (0.52%)	137.00 (0.93%)	81.4%
9	Email	92 (0.43%)	7 (0.04%)	46 (1.48%)	2m 12s	1.15	1,759 (0.76%)	188.00 (1.27%)	57.69%
10	Organic Video	2 (<0.01%)	2 (0.01%)	0 (0%)	51s	1.00	33 (0.01%)	1.00 (<0.01%)	50%

Figure 3: Total users with their engagement and event contribution across channels using GA4 for the website

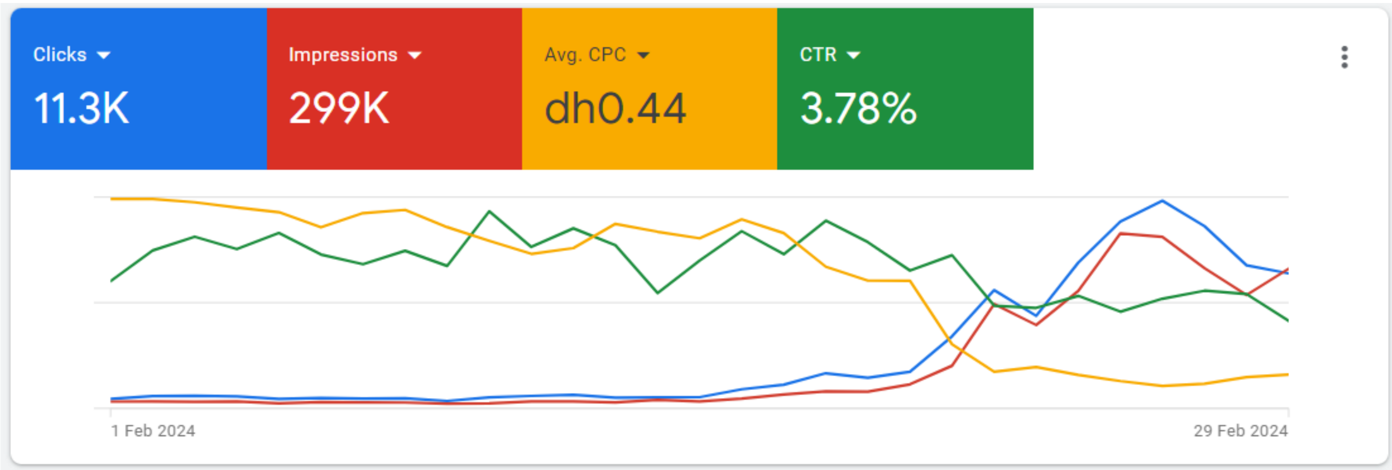


Figure 4: Measuring Cost-per-click and Click-through rate using Google Ads

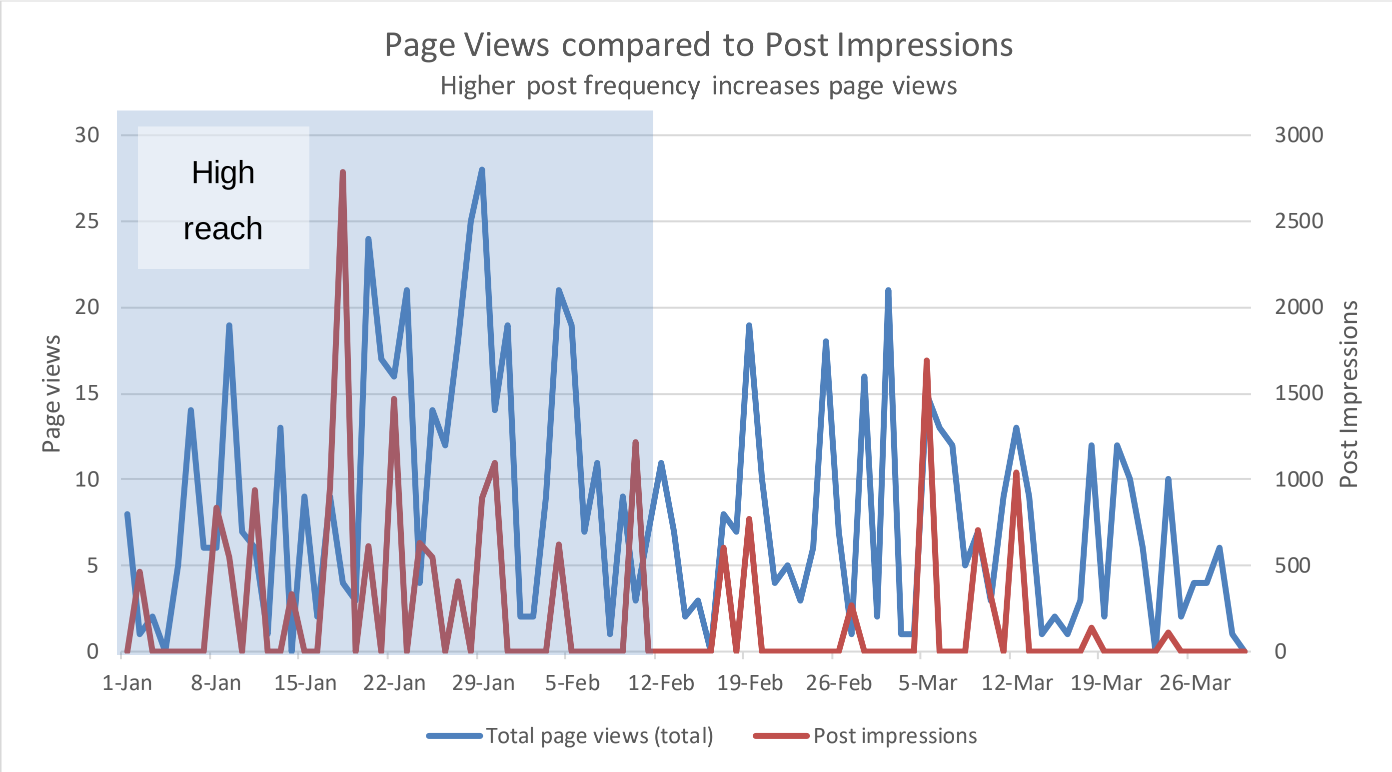


Figure 5: Correlation between page views and post impressions over time for TUIBS LinkedIn page

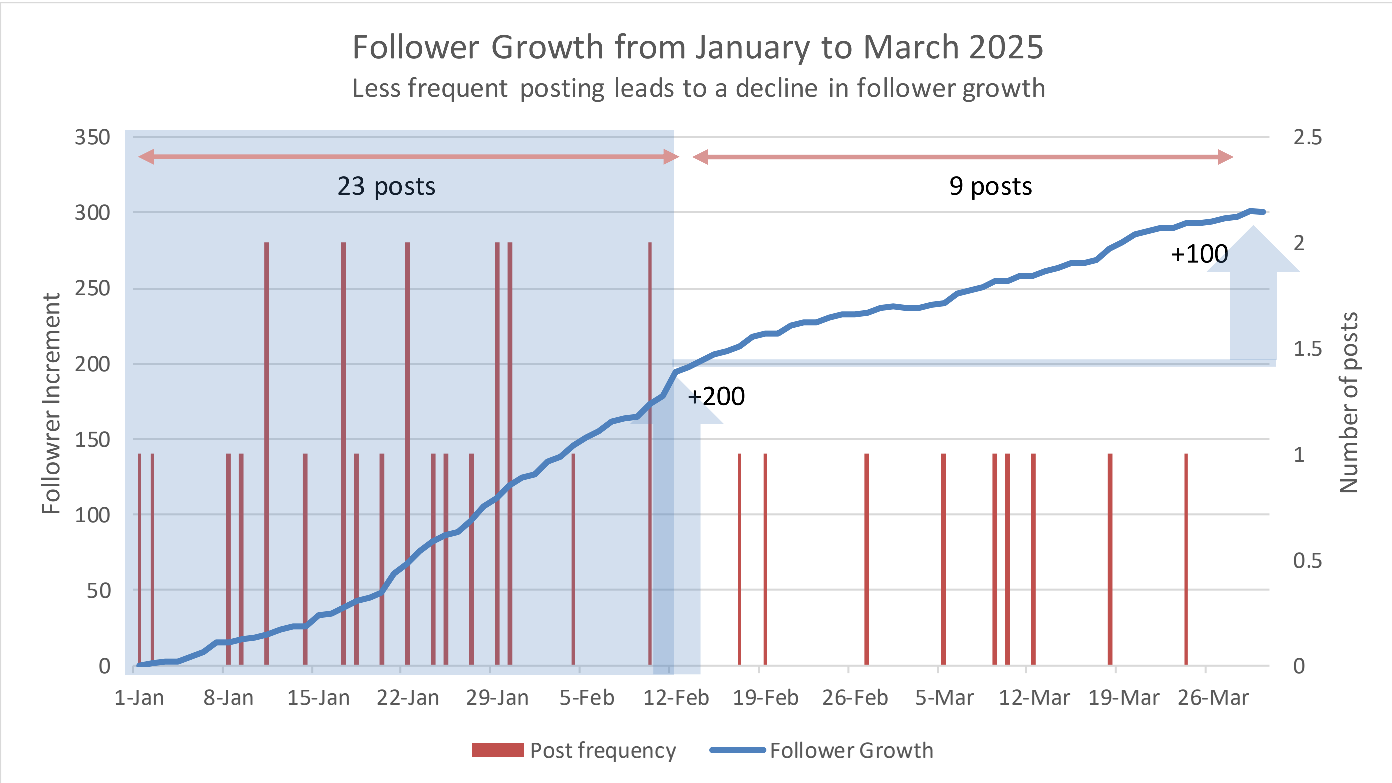


Figure 6: LinkedIn follower growth over time

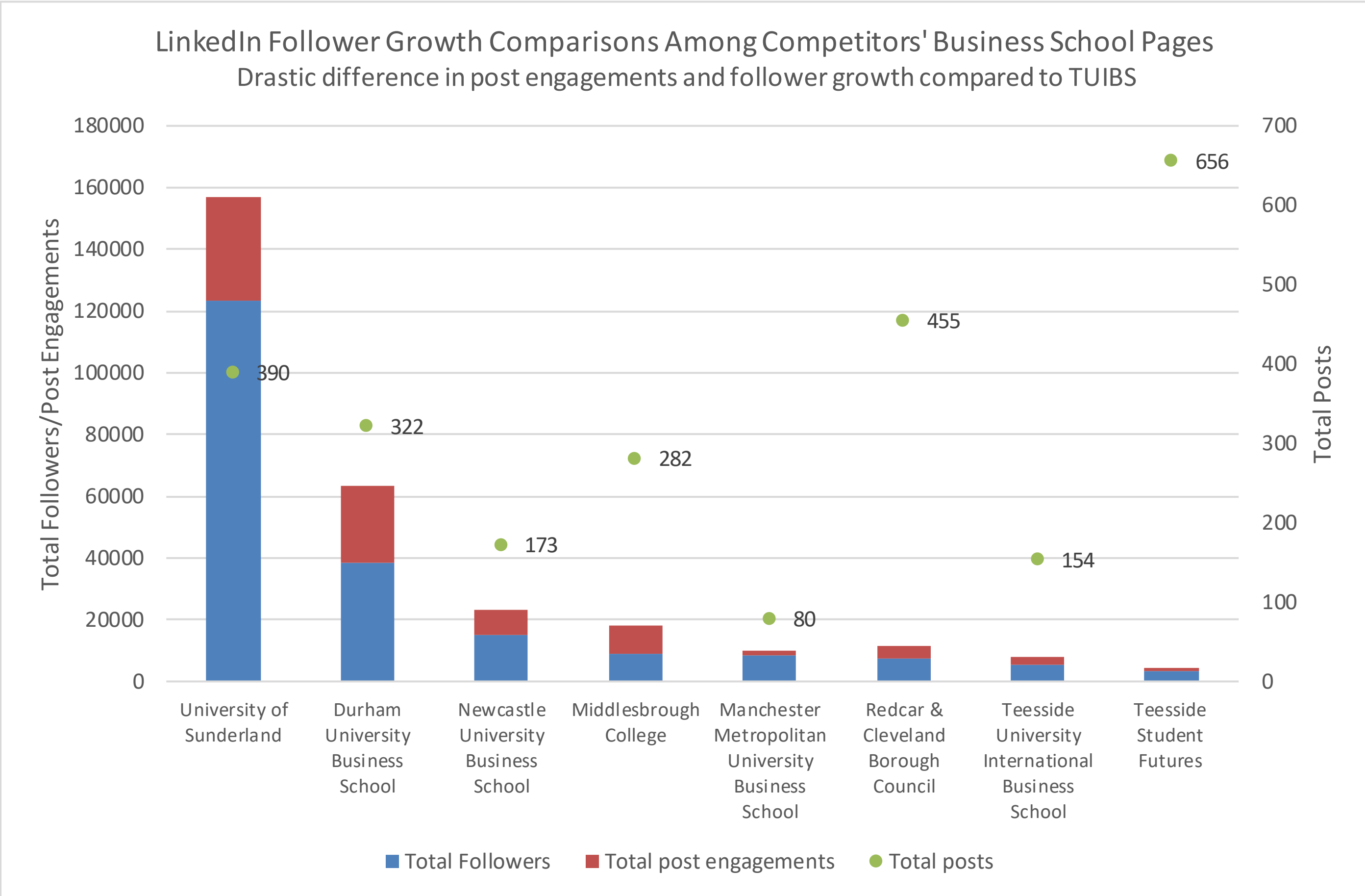


Figure 7: LinkedIn pages growth comparisons among competitors' business schools

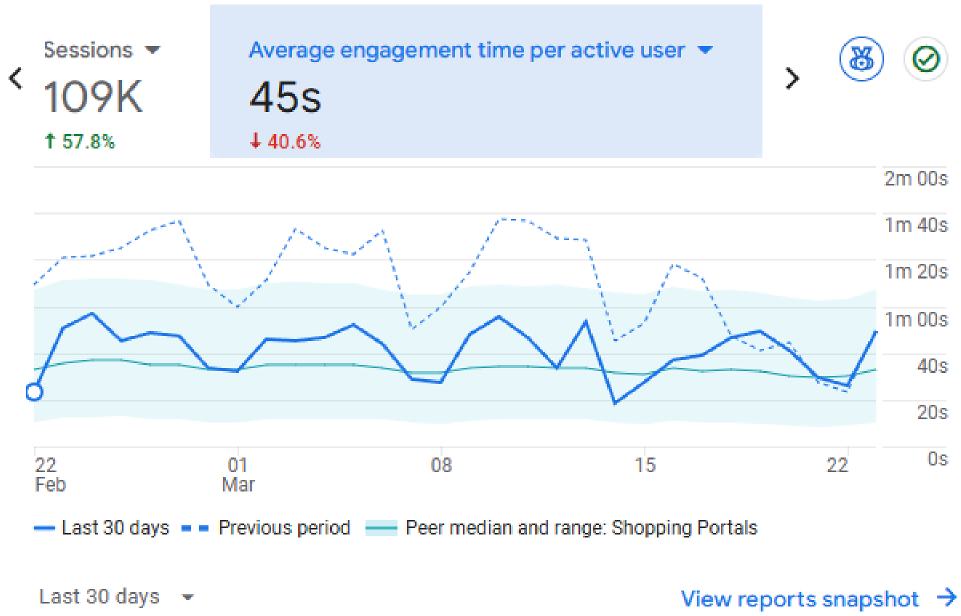
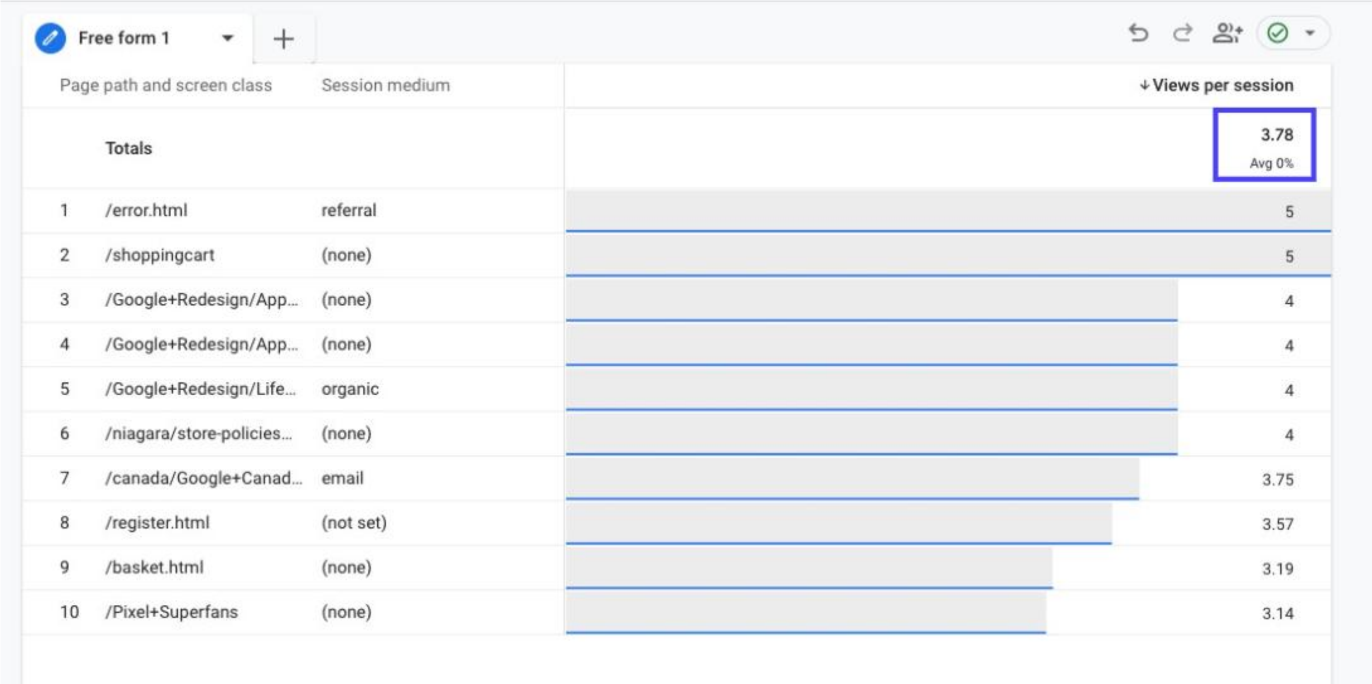


Figure 8: Average engagement time per active user in GA4



Free form 1

	Page path and screen class	Session medium	↓Views per session
	Totals		3.78 Avg 0%
1	/error.html	referral	5
2	/shoppingcart	(none)	5
3	/Google+Redesign/App...	(none)	4
4	/Google+Redesign/App...	(none)	4
5	/Google+Redesign/Life...	organic	4
6	/niagara/store-policies...	(none)	4
7	/canada/Google+Canad...	email	3.75
8	/register.html	(not set)	3.57
9	/basket.html	(none)	3.19
10	/Pixel+Superfans	(none)	3.14

Figure 9: Tracking pages viewed per session for active users

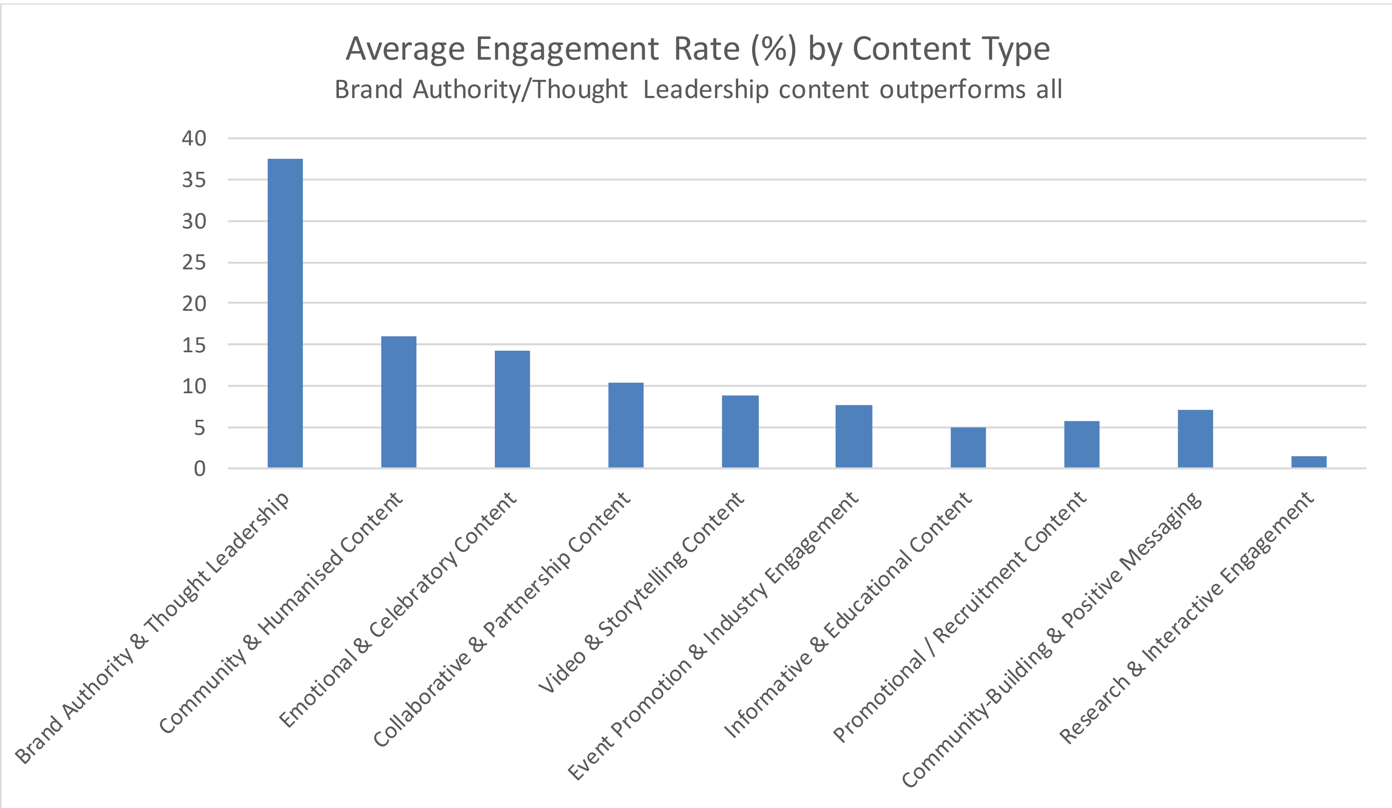


Figure 10: Engagement rate comparisons of the most common content types in TUIBS LinkedIn page from January 1st to March 30th

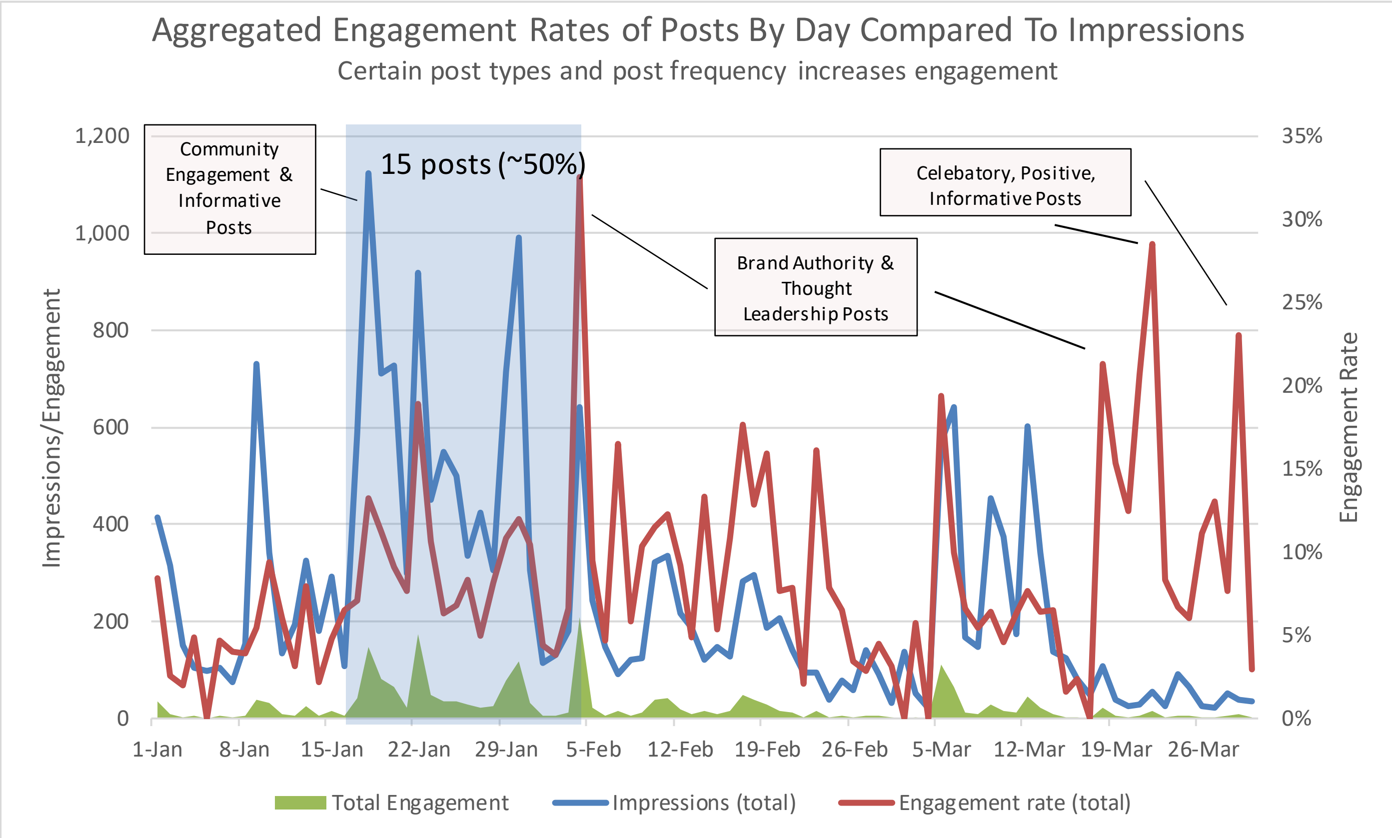


Figure 11: Engagement rates corresponding to total impressions over time for TUIBS LinkedIn page

F F Free form 3 +

	Session source / medium	↓Sessions	Total users	Conversions	Session conversion rate	User conversion rate
	Totals	139,800 100.0% of total	81,713 100.0% of total	1,924 100.0% of total	1.1% 100.0% of total	1.7% 100.0% of total
1	google / organic	114,459	69,069	803	0.5%	0.8%
2	(direct) / (none)	10,224	6,409	563	4.4%	6.6%
3	am-convertkit / email	5,468	2,960	135	2.2%	4.2%
4	youtube.com / video	2,924	1,864	229	6.2%	9.5%
5	bing / organic	1,354	927	12	0.4%	0.7%
6	duckduckgo / organic	716	497	2	0.3%	0.4%
7	(not set) / (not set)	652	588	7	0.9%	1.0%
8	deadlinefunnel / email	536	337	25	4.3%	6.9%
9	analytics mania ebook / pdf	434	220	34	5.1%	10.3%
10	student_mailer / email	320	123	3	0.9%	2.6%

Figure 12: Tracking conversion rate for sessions and users in their journey

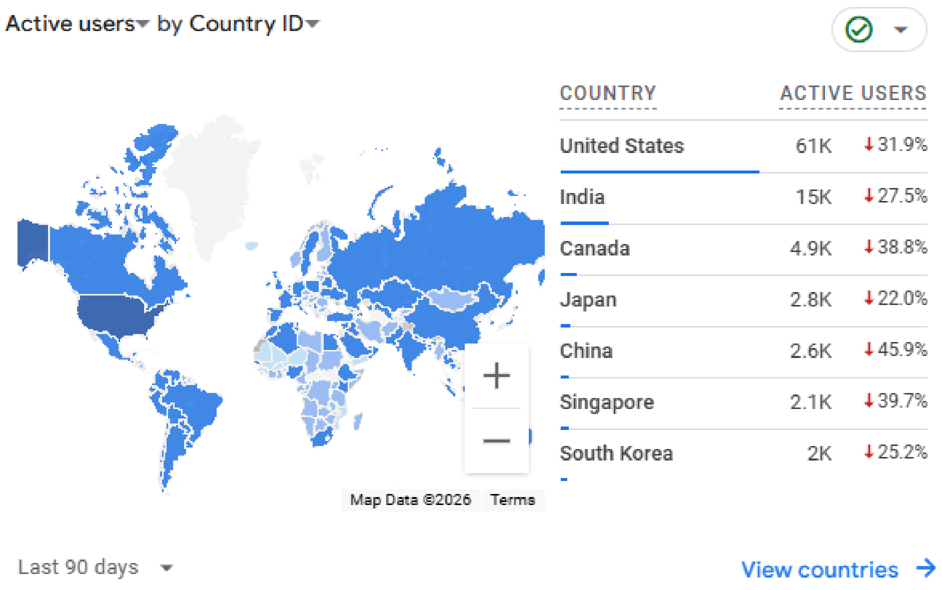


Figure 13: Top active users from countries using GA4

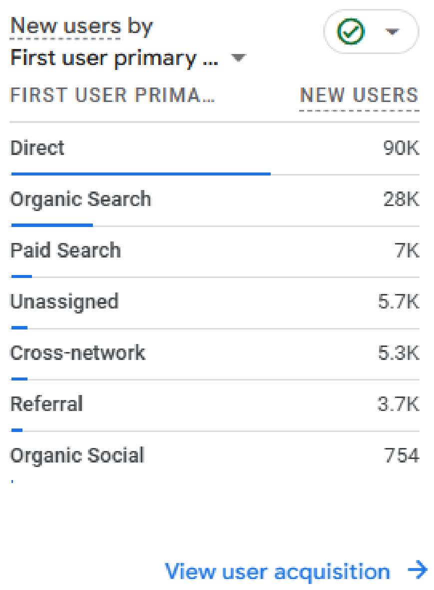


Figure 14: First users across channels

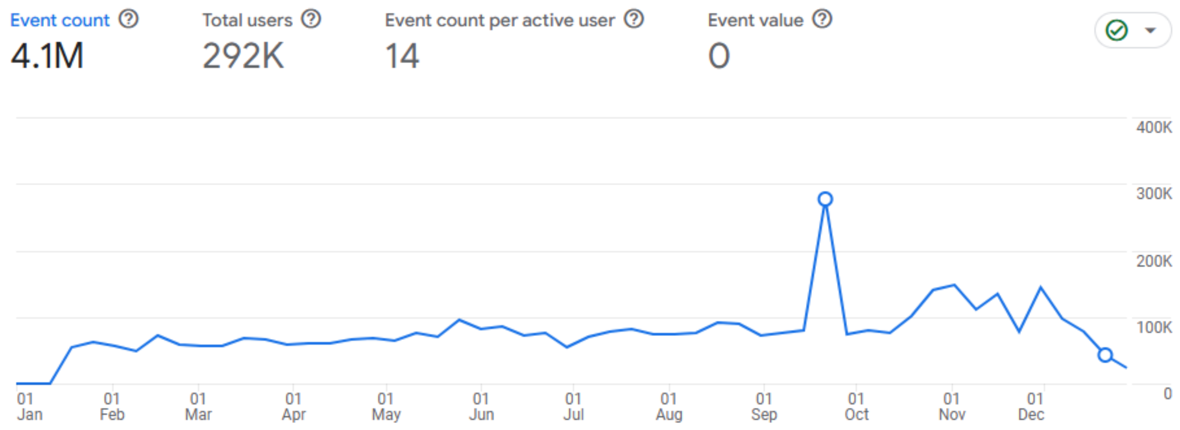


Figure 15: Event counts across active users

	Page path and screen class	Views	Active users	Online active user views	Average online active user engagement time	Event count (All events)	Key events (All events)	Total revenue
	Total	729,383 (100% of total)	158,971 (100% of total)	4.59 (Avg 0%)	1m 06s (Avg 0%)	2,718,697 (100% of total)	176,792.00 (100% of total)	$405,846.83 (100% of total)
1	/	168,960 (23.16%)	119,404 (75.11%)	1.42	11s	584,304 (21.49%)	1.00 (<0.01%)	$0.00 (0%)
2	/shop/new	46,279 (6.34%)	21,383 (13.45%)	2.16	46s	208,829 (7.68%)	10.00 (<0.01%)	$0.00 (0%)
3	/shop/apparel/mens	32,209 (4.42%)	12,737 (8.01%)	2.53	1m 12s	159,692 (5.87%)	8.00 (<0.01%)	$0.00 (0%)
4	/checkout	30,288 (4.15%)	6,894 (4.34%)	4.39	1m 58s	80,008 (2.94%)	2,543.00 (1.44%)	$397,222.70 (97.88%)
5	/search	22,082 (3.03%)	8,993 (5.66%)	2.46	43s	52,397 (1.93%)	2.00 (<0.01%)	$0.00 (0%)
6	/shop/clearance	21,305 (2.92%)	11,327 (7.13%)	1.88	28s	63,967 (2.35%)	11.00 (<0.01%)	$0.00 (0%)
7	/shop/apparel	18,914 (2.59%)	10,284 (6.47%)	1.84	54s	95,370 (3.51%)	2.00 (<0.01%)	$0.00 (0%)
8	/shop/lifestyle/bags	14,966 (2.05%)	9,347 (5.88%)	1.60	26s	55,443 (2.04%)	8.00 (<0.01%)	$0.00 (0%)
9	/shop/lifestyle/drinkware	13,721 (1.88%)	7,962 (5.01%)	1.72	35s	56,989 (2.1%)	3.00 (<0.01%)	$0.00 (0%)
10	/shop/lifestyle/fun-and-games	13,443 (1.84%)	8,985 (5.65%)	1.50	18s	40,180 (1.48%)	6.00 (<0.01%)	$0.00 (0%)

Figure 16: Tracking user activity and engagement across different pages

Plot rows | Search... | Rows per page: 10 | Go to: 1 | 1-10 of 13

	Primary channel...Channel Group)	All conversions	Ads cost	Cost per all conversions (by int. time)	Ads impressions	Ads clicks	Ads cost per click	Total revenue (by int. time)	Return on ad spend (by int. time)
	Total	89,200.36 (100% of total)	$6,797.57 (100% of total)	$0.08 (Avg 0%)	268,477 (100% of total)	11,892 (100% of total)	$0.57 (Avg 0%)	$144,966.71 (100% of total)	21.33 (Avg 0%)
1	Direct	59,355.00 (66.54%)	$0.00 (0%)	$0.00	0 (0%)	0 (0%)	$0.00	$93,298.92 (64.36%)	0.00
2	Organic Search	16,747.48 (18.78%)	$0.00 (0%)	$0.00	0 (0%)	0 (0%)	$0.00	$31,974.85 (22.06%)	0.00
3	Cross-network	6,189.15 (6.94%)	$674.27 (9.92%)	$0.11	55,683 (20.74%)	3,390 (28.51%)	$0.20	$4,880.34 (3.37%)	7.24
4	Paid Search	2,633.37 (2.95%)	$463.12 (6.81%)	$0.18	4,078 (1.52%)	935 (7.86%)	$0.50	$6,566.80 (4.53%)	14.18
5	Referral	2,235.52 (2.51%)	$0.00 (0%)	$0.00	0 (0%)	0 (0%)	$0.00	$5,734.36 (3.96%)	0.00
6	Organic Social	795.16 (0.89%)	$0.00 (0%)	$0.00	0 (0%)	0 (0%)	$0.00	$974.15 (0.67%)	0.00
7	Unassigned	572.76 (0.64%)	$0.00 (0%)	$0.00	0 (0%)	0 (0%)	$0.00	$426.81 (0.29%)	0.00
8	Organic Shopping	557.73 (0.63%)	$0.00 (0%)	$0.00	0 (0%)	0 (0%)	$0.00	$853.08 (0.59%)	0.00
9	Organic Video	73.91 (0.08%)	$0.00 (0%)	$0.00	0 (0%)	0 (0%)	$0.00	$122.16 (0.08%)	0.00
10	Email	40.28 (0.05%)	$0.00 (0%)	$0.00	0 (0%)	0 (0%)	$0.00	$135.23 (0.09%)	0.00

Figure 17: Tracking conversion performance using GA4

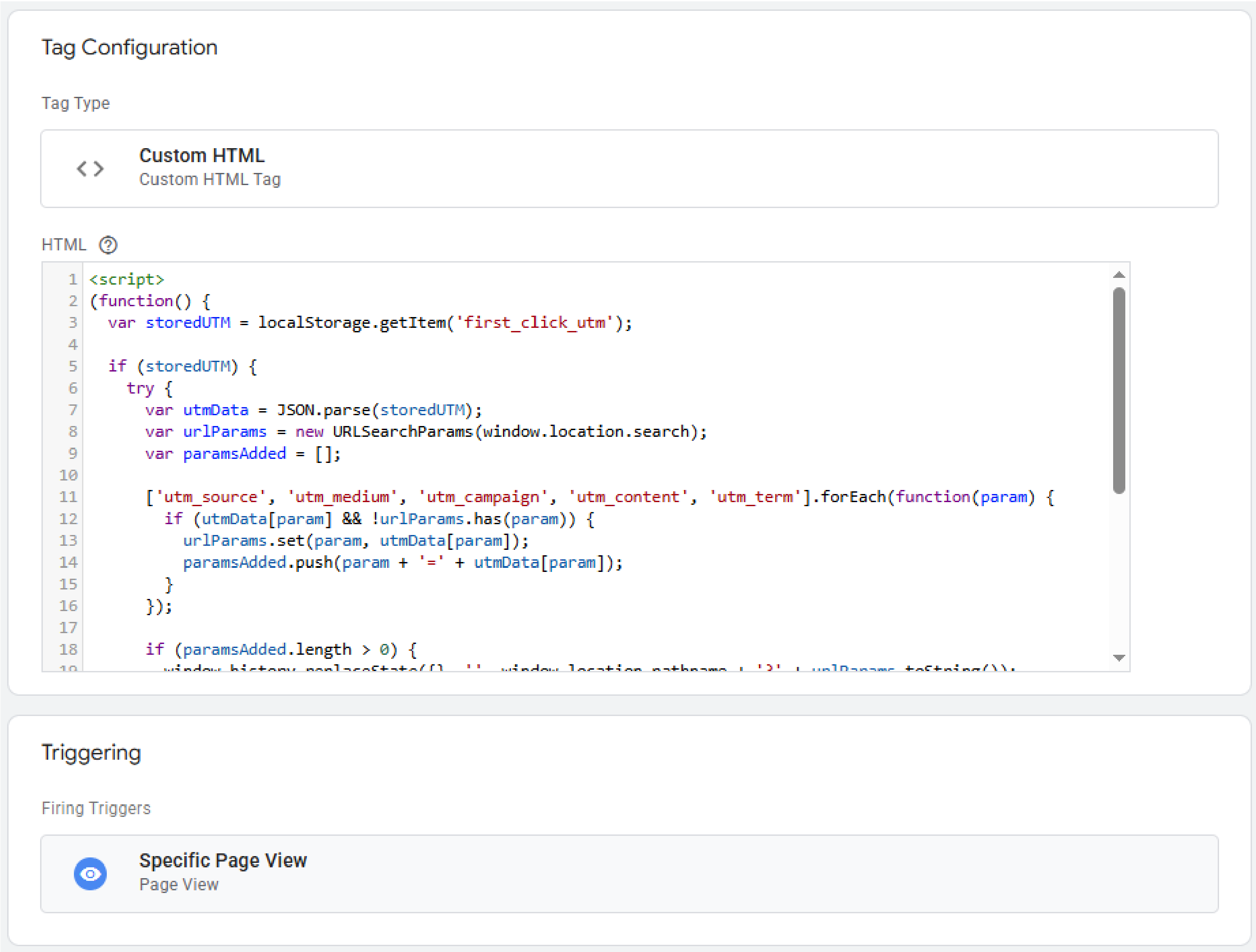


Figure 18: Setting up a UTM parameter and tag in the HTML header

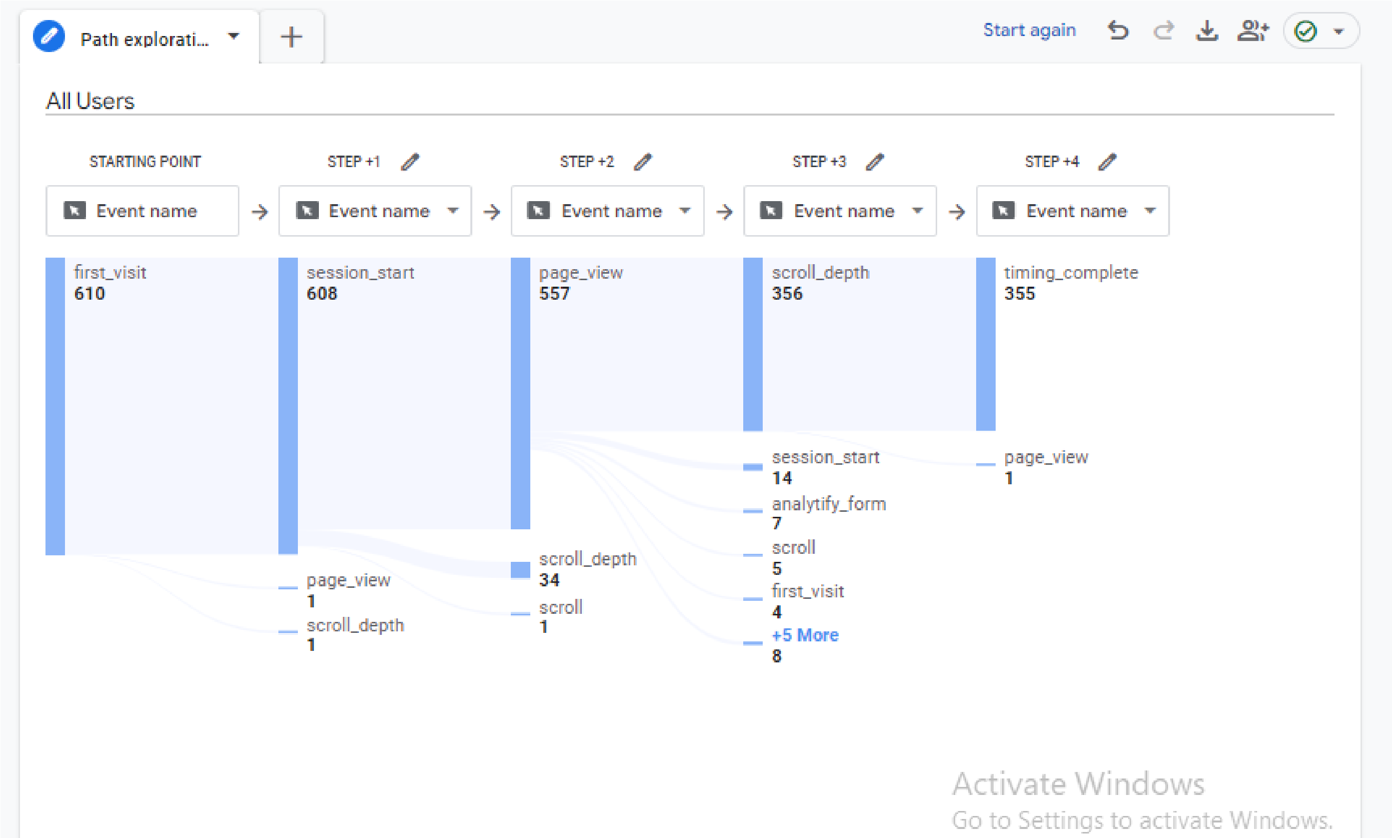


Figure 19: User-journey tracking using GA4

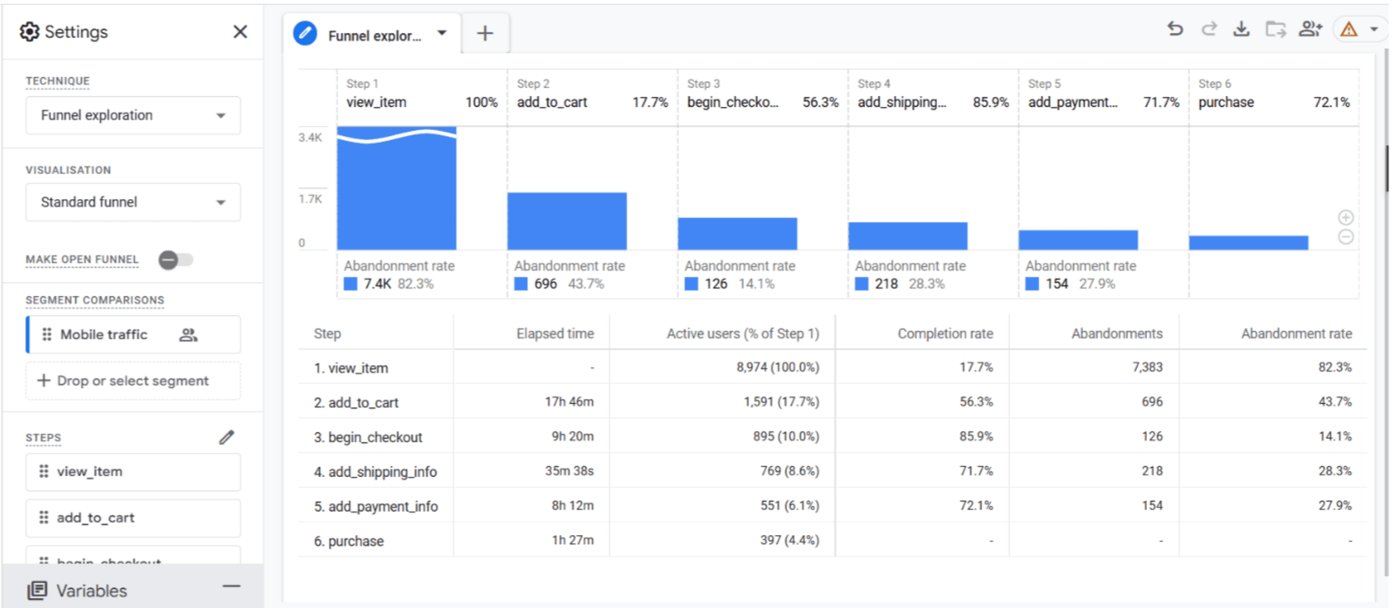


Figure 20: Abandonment rates across different pages in the funnel