# A Scalable Approach to Marketing Funnel Modeling: Cross-Industry Insights from LinkedIn

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**Abstract.** Using a proprietary LinkedIn subset of data containing over 200 million advertisement interactions across millions of users, we model marketing funnel stages based on industry, called professional user demographics. Both demographic-specific funnels and a cross-demographic model to align and compare engagement patterns across industries are introduced. Our findings reveal that while the funnel structure remains broadly similar and stable, significant professional demographic variance exists in flow volumes, transition velocities, and stage occupancy. We identify key transition pathways, the strategic role of no-engagement stages, and cyclical user flows indicating loyalty or disengagement. These insights offer actionable guidance for marketers seeking to optimize targeting, timing, and content strategies based on audience-specific funnel behavior.

**Keywords:** Marketing Funnel, Social Media Analytics, Behavioral Clustering.

## 1 Introduction

Professional demographics play a central role in shaping social media advertising strategies [10]. Platforms like LinkedIn have transformed digital marketing—especially in B2B contexts—by enabling professional demographic-based targeting. Yet, advertisers often lack clear insight into how these demographic factors do or don't influence real-world user engagement and progression through the marketing funnel [2,9]. This gap is particularly relevant given that industries vary widely in sales cycles and conversion behaviors; sectors like construction or insurance involve long, complex decision-making, while retail and technology may feature shorter, more transactional cycles [2,7].

Industry approaches to the marketing funnel typically emphasize lead prioritization strategies aimed at improving business outcomes by identifying higher-quality B2B leads based on demographic fit [13]. These models often follow a multi-stage structure in which leads are first generated, then scored using demographics, and subsequently engaged by sales representatives [14]. While such frameworks effectively mirror operational sales processes, they generally focus on discrete outcomes rather than modeling incremental user changes across the entire funnel. In contrast, the present study adopts a holistic, end-to-end perspective, aiming to enhance our understanding of how leads transition between stages within the B2B marketing funnel and the role demographics play in the progression.

This study introduces a novel, data-driven approach using LinkedIn engagement data to model professional demographic-specific marketing funnels across industries. While industrial outcomes are of interest, user-level engagements drive LinkedIn's ad ecosystem, making user demographics critical to analysis. We ask and answer: "*How does the professional demographic of industry affect the flow size and velocities in the marketing funnel?*" and "*How do metrics vary across professional demographics within the funnel?*". By uncovering how industries and their user bases interact differently across funnel stages, this research offers practical insights for refining targeting, sequencing, and advertising strategy [11]. The following sections outline our clustering methodology, funnel modeling, and implications for real-world campaign design.

## 2 Theoretical Background

The marketing funnel is a foundational theory in digital advertising, outlining the stages users follow from initial exposure to conversion [8]. While widely accepted in concept, the funnel's structure and flow vary significantly in practice, particularly in B2B contexts where factors such as industry and company size change purchase frequency and deal size [7,9]. Flow modeling of users is well-established for the marketing funnel [2,7,9]. These demographic attributes affect both how long users remain in each stage and their likelihood of progression [2]. Platforms like LinkedIn rely on professional demographic segmentation to optimize targeting [7,11]. Users from digitally native sectors tend to move more fluidly through the funnel, while those in traditional industries like government progress more gradually [7,10]. Although funnel stages (e.g., impressions, clicks, conversions) remain conceptually stable [5], their size, transition velocity, and frequency are heavily shaped by demographic context [2].

Behavioral modeling supports these findings. Marvasti [9] used Hidden Markov Models to classify B2B buyer journeys, showing clear demographic variation. Engagement depth and flow efficiency differ between industries offering fast-moving, low-cost goods and those with complex, capital-intensive products [2]. Social media further amplifies these dynamics. Early interactions like impressions and likes may indicate interest, but deeper engagements—comments, lead submissions—are more predictive of conversion [2,6]. Importantly, user progression is not always linear; some users cycle backward or drop off entirely [1,11]. These complexities highlight the need for marketers to adapt funnel strategies to demographic behavior and campaign goals.

## 3 Data and Methodology

This study leverages a proprietary dataset from LinkedIn, comprising user interactions with advertisements over a 12-month period. The dataset consists of random subsets of members, across demographics, with activity over the study period and contains over 200 million interactions from the LinkedIn network, providing a robust foundation for analyzing professional demographic differences within the marketing funnel. All data is consented profile information that adheres to member settings and privacy.

### 1.3 Data

The dataset emphasizes two critical professional demographic variables relevant to B2B marketing: industry and company size. Industry demographics reflect key differences in product needs, sales cycles, and purchasing behaviors across sectors [2,7]. To analyze user interaction patterns across these professional demographic segments, the dataset includes essential engagement metrics such as impressions, clicks, likes, shares, comments, and conversions. Data is aggregated at monthly intervals per user, enabling effective analysis of longitudinal behavioral trends and user transitions within the marketing funnel.

Monthly granularity also addresses key methodological challenges. Rather than storing raw user-level data, we retain essential summary metrics such as cluster sizes, transition probabilities, and flow velocities. This approach offers practical and actionable insights while ensuring alignment with privacy standards and ethical data handling practices [4]. This study explored daily and weekly granularities, which provide strong short-term predictive power of future user engagements but are too noisy to model long-term cluster stability with transitions.

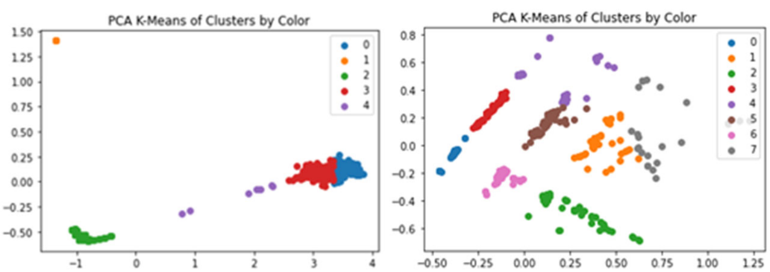
### 2.3 Clustering and Cross-Demographic Funnel Creation

This study employs an unsupervised clustering approach using KMeans clustering to derive marketing funnel stages directly from observed user engagement data, generating eight distinct clusters. These clusters range from baseline engagement to high-intensity interactions, including conversions and deeper funnel activities [2,7]. The application of KMeans clustering enables a data-driven identification of distinct user-behavior segments without imposing predefined business categories, allowing the analysis to organically reveal meaningful engagement patterns [3]. This method has previously demonstrated effectiveness in capturing complex user interactions and marketing funnel transitions in social media contexts, including LinkedIn [12].

### 3.3 Challenges and Solutions in Model Alignment and Validation

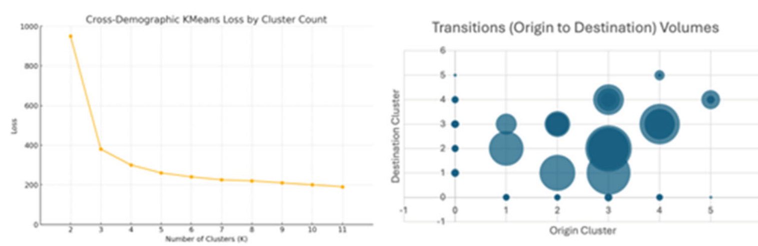
A key methodological challenge is aligning and comparing funnel stages across multiple demographic-specific models. Since each demographic funnel are generated using a separate KMeans clustering process, the resulting clusters are distinct, making direct comparisons difficult due to variations in cluster definitions and centers. To address this, we introduced a cross-demographic clustering step. We applied a secondary KMeans model to the original cluster centers from each demographic-specific model, grouping them into a unified set of cross-demographic clusters. This allows for systematic alignment of similar engagement patterns across demographics, enabling consistent and meaningful comparisons. A two-dimensional PCA transformation (Figure 1) illustrates the results of this approach, revealing distinct and well-separated cluster groupings. The attribution metrics provide clear separation of demographic groups within the marketing funnel and confirm that the cross-demographic clustering captured shared behavioral patterns while preserving differences across demographic groups.

**Fig. 1.** Cross-Demographic KMeans Clustering Before (a) and After (b) a 2-D PCA Transformation




To preserve the detailed behavioral distinctions from the original demographic-specific models, we selected eight clusters (k = 8) for the cross-demographic model. Although the elbow method and PCA suggested that fewer clusters (e.g., 3 or 4) might suffice, we prioritized retaining meaningful engagement variation over model simplicity. As shown in Figures 1b and 2, while fewer clusters would reduce complexity, using k = 8 maintained critical nuances essential for practical insight. The Silhouette was measured across each demographic's clusters as validation to ensure points within a cluster are close and far away from other clusters.

**Fig. 2.** Cross-Demographic KMeans Loss by Cluster Count (a) and Cluster Transitions Across All Demographics (b)




A key part of our methodology involved validating the stability and interpretability of user behavior clusters and their transitions within the marketing funnel. We used several strategies to confirm that clusters reflected real engagement patterns rather than arbitrary groupings. First, we analyzed user transitions across multiple months. Frequent, recurring multi-cluster transitions can indicate meaningful behavioral shifts, showing that the funnel captures evolving engagement over time. We also assessed the funnel's overall structure to ensure alignment with theoretical expectations, namely, a wide entry point of low-engagement users narrowing to fewer, high-engagement conversions. This structure reflects established models of progression in digital marketing.

To confirm the funnel captured real-world complexity, we looked for cyclical behaviors, such as users moving from deep to shallow stages, signaling disengagement or re-engagement. Lastly, we confirmed structural consistency across demographics. While some variation was expected, the presence of stable patterns across groups supports the generalizability and robustness of our approach.

# 4 Results

## 4.3 Cluster Identification and Funnel Stages

The clustering analysis generated eight distinct clusters representing different stages of user engagement within the marketing funnel. Below, each cluster is summarized based on key engagement metrics, clearly distinguishing between high, medium, low, and baseline engagement levels (Table 1).

**Table 1.** Table captions should be placed above the tables.

| Cluster | Engagement Level | Description | Key Engagement Metrics |
|---|---|---|---|
| **2** | Baseline | Less active users | Baseline activity |
| **0** | Low | Minimal engagement | Occasional likes, clicks, impressions |
| **4** | Medium | Moderate engagement | Moderate branding activity, clicks, preview downloads |
| **6** | Medium | Moderate branding-focused engagement | Moderate impressions, branding interactions |
| **5** | High | Branding-oriented engagement | High comment activity, likes, shares |
| **1** | High | Active engagement, lower lead generation | High clicks, shares, follows, fewer lead conversions |
| **3** | High | Deep-funnel activity | High lead generation, conversions, job applications |
| **7** | Highest | Highly active across all metrics | Very high impressions, clicks, shares, conversions |

**Cluster 2: Baseline Engagement**

Cluster 2 represents less active users with fewer interactions, either on the LinkedIn platform or external websites associated with LinkedIn advertisements. This cluster provides a baseline, reflecting periods where users show less engagement with advertiser content (Figure 3).

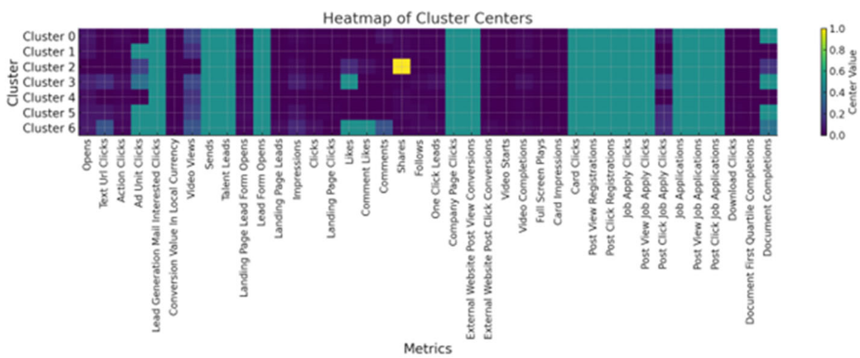
**Fig. 3.** Example of Metric and Cluster Centers for the Accounting Demographic

| Metric / Clusters | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|
| Opens | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.82 | 1.00 | 0.00 |
| Text URL Clicks | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.93 | 0.00 |
| Action Clicks | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.91 | 1.00 | 0.00 |
| Ad Unit Clicks | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.40 | 0.00 |
| Lead Generation Mail Interested Clicks | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.00 |
| Conversion Value In Local Currency | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.00 |
| Video Views | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.86 | 1.00 | 0.00 |
| Sends | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.84 | 1.00 | 0.00 |
| Talent Leads | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.00 |
| Landing Page Lead Form Opens | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.00 |
| Lead Form Opens | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 |
| Landing Page Leads | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 | 0.00 |
| Impressions | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.97 | 0.00 |

## Cluster 0: Some Engagement

Cluster 0 is characterized by fewer interactions. Users in this cluster display occasional, isolated engagements, such as impressions or minor interactions like likes and clicks. These interactions occur infrequently and represent lower user interest (Figure 4).

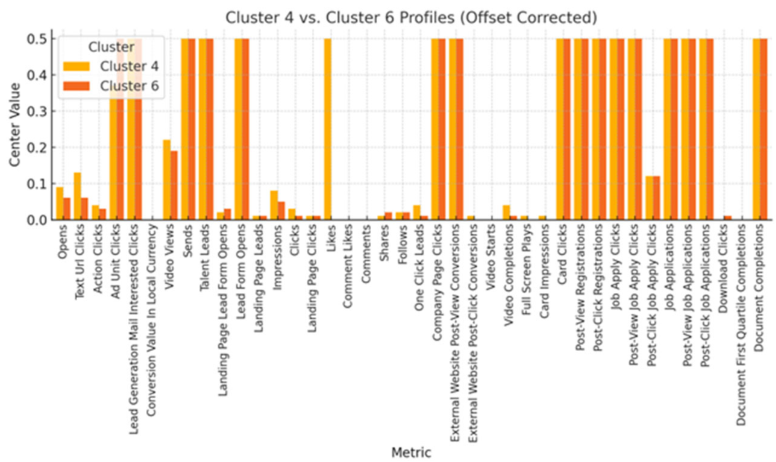
**Fig. 4.** Heatmap of Metric Values by Cluster




## Medium Engagement Clusters (Clusters 4 and 6)

Clusters 4 and 6 represent moderate engagement, indicating user interactions that are more consistent but limited in scope. Cluster 4 shows moderate activity, with users engaging occasionally in branding activities like clicks, preview downloads, and minor interaction such as shares or comment likes (Figure 5). Cluster 6 is similarly positioned, emphasizing moderate branding interactions, with slightly higher activity in shares, impressions, and engagement on posts (Figure 5).

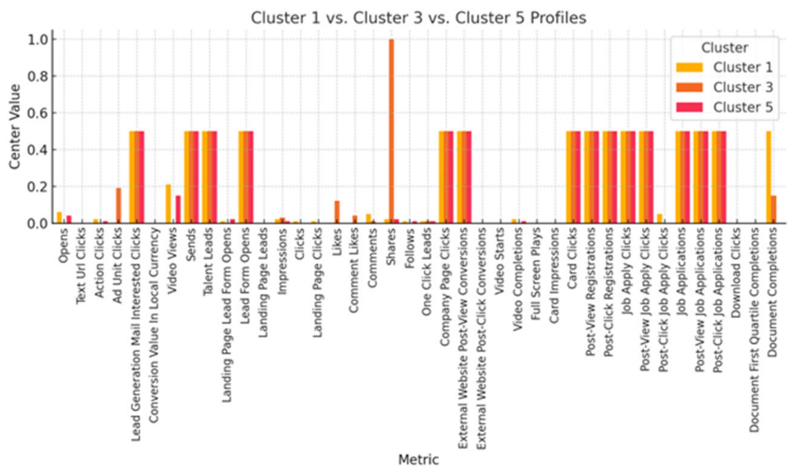
**Fig. 5.** Metric Values for Cluster 4 and 6 Centers (Medium Engagement Cluster)




**High Engagement Clusters (Clusters 1, 3, and 5)**

Clusters 1, 3, and 5 demonstrate high-level engagement, each with distinct interaction profiles. Cluster 1 emphasizes general high engagement across common advertising metrics such as impressions, clicks, and follows but notably has lower performance on lead generation metrics (Figure 6). Cluster 3 stands out as a deep-funnel activity cluster, characterized by significant lead generation, conversions, and job-related metrics. Users in this cluster actively engage in behaviors closely linked to potential purchases or deeper business interactions (Figure 6). Cluster 5 is branding-oriented, displaying high activity around comments, likes, and shares, suggesting strong user interest and engagement with the brand's content and community activities (Figure 6).

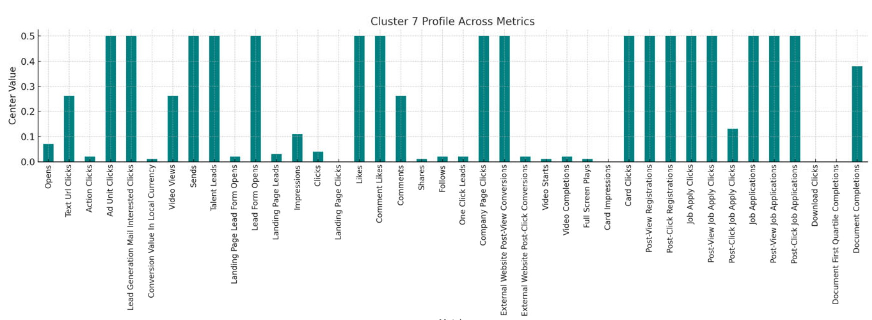
**Fig. 6.** Metric Values for Cluster 1, 3, and 5 Centers (1 = High Engagement, Lower Leads, 3 = Deep Funnel Activity, 5 = Branding-Oriented)




**Cluster 7: Highest Engagement**

Cluster 7 represents the pinnacle of user engagement. Users classified here demonstrate exceptionally high interactions across virtually all measured engagement metrics. This includes high impressions, clicks, shares, likes, and conversions, representing the most active and engaged segment within the dataset. Members in this cluster display strong signals of brand affinity and a likelihood of conversion (Figure 7).

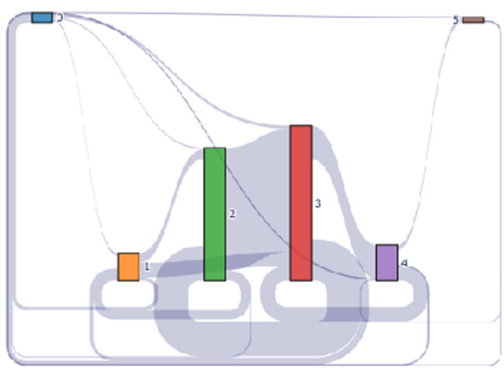
**Fig. 7.** Metric Values for Cluster 7 Centers (Highest Engagement Cluster)




## 5.3 Cluster Similarities and Differences Across Demographics

Demographic-specific analyses of user flow volumes and transitions among funnel stages provided insights into how professional demographic characteristics influence engagement dynamics. Certain clusters demonstrated strong interconnections, indicating consistent user transitions and defining clear pathways through the funnel stages. Two primary engagement pathways emerged prominently from the data. The first major pathway captures user progression from low engagement (Cluster 0) toward higher-engagement clusters (Clusters 1, 4), ultimately leading to deep funnel activities characterized by lead generation and conversions (Cluster 3). The second significant pathway describes a branding-oriented trajectory, moving users from high branding activity (Cluster 5) to moderate engagement (Cluster 4), eventually funneling into deeper stages of the marketing funnel (Cluster 3). Visualizations of these patterns clearly illustrated key transition pathways among funnel stages (Figure 8).

**Fig. 8.** Sankey Diagram of the Flow within LinkedIn's Aggregate Marketing Funnel




The patterns shown are based on a subset of users and do not generalize site wide. This paper also simplifies each cluster by particular engagements, but users can demonstrate a variety of engagement and still be classified within one particular cluster, so the cluster data should not be used to infer about user statistics. This paper demonstrates how simplified marketing funnel models can offer a nuanced understanding of the B2B marketing funnel in different industries.

The distribution of users across funnel stages highlights meaningful engagement patterns. In the original on-platform view, based on this subset of users, approximately 35% of users are grouped in Cluster 0, representing baseline engagement. Cluster 3, which captures deeper-funnel behaviors such as conversions and lead generation, includes about 29% of users. Medium and branding-oriented engagement clusters make up roughly 32%, while a small 4% of users fall into a lower engagement group, indicating limited on-platform activity.

When we expand the view by incorporating LAN data which captures off-platform advertising activity the overall structure of the funnel becomes more nuanced and conversion-focused. Rather than indicating reduced engagement, this expanded view reflects a broader set of user actions and outcomes, particularly those deeper in the funnel. While Cluster 3 now includes 24% of users, and Cluster 0 accounts for 26%, these shifts are due to a refined focus on conversion and lead-related behaviors, which are naturally more selective. The addition of LAN data surfaces a wider reach and more engagement touchpoints, enabling a more comprehensive understanding of the user journey beyond initial exposure.

### 6.3 Demographic-Specific Funnel Structures

namics of marketing funnels vary across industries. Using Sankey diagrams (Figures 9a–g), we visualize transitions between funnel stages for sample industries, highlighting variations in funnel complexity, stage distribution, and flow intensity. While most industries share structural elements such as early-stage branding and deeper conversion clusters, each funnel profile is distinct. For instance, the Dance Companies demographic shows a large baseline engagement stage followed by clear transitions into deeper stages, whereas Geothermal Electric Power Generation has a more balanced distribution, suggesting consistent engagement throughout the funnel. Some industries exhibited simpler funnels due to limited engagement or smaller data volumes. Computer and Network Security, for example, shows fewer transitions, indicating a narrow or highly targeted campaign strategy. Education Administration features dominant flows between only two or three stages. In contrast, Retail Recyclable Materials & Used Merchandise and Breweries have more complex funnels, with strong transitions into the highest engagement clusters, suggesting greater responsiveness to advertising content.

Funnels that incorporate off-platform attribution data—such as external site activity or third-party lead conversions—show significantly more complex structures. For example, Waste Treatment and Disposal shows a simplified funnel without attribution data, while Breweries and Retail exhibit deeper, more nuanced pathways when full data are available. Across industries, a few consistent patterns emerged:

- Cluster 3 (deep-funnel, high engagement) consistently receives transitions from multiple other stages.
- Cluster 0 (lower engagement) often serves as a central hub for users but can also be a reentry point into the funnel.
- Cyclical transitions, where users return to prior stages, may indicate loyalty, re-engagement, or delayed decision-making.

These findings reinforce that while the core structure of the funnel is stable, differences in engagement intensity and flow behavior across demographics are substantial. For marketers, this underscores the need to align funnel design, content strategy, and conversion timing with the behavioral patterns of specific industries.

## 5 Discussion of Results

This study presents a practical framework for analyzing how professional user demographics influence engagement and transitions within B2B marketing funnels. While funnel structures were consistent across demographics, we found significant variation in flow volumes, stage distribution, and transition dynamics—insights that help refine targeting, budgeting, and content strategy. Our data-driven clustering approach offers flexibility by aligning funnel stages with actual user behavior, avoiding rigid assumptions. By summarizing engagement patterns rather than storing raw user data, the method remains privacy-compliant [2,4] while supporting actionable analysis. Industry practitioners can apply these insights to benchmark performance, set realistic conversion goals, and reconfigure campaigns based on demographic-specific engagement patterns. Only professional demographics with a minimum of 10k users are included.

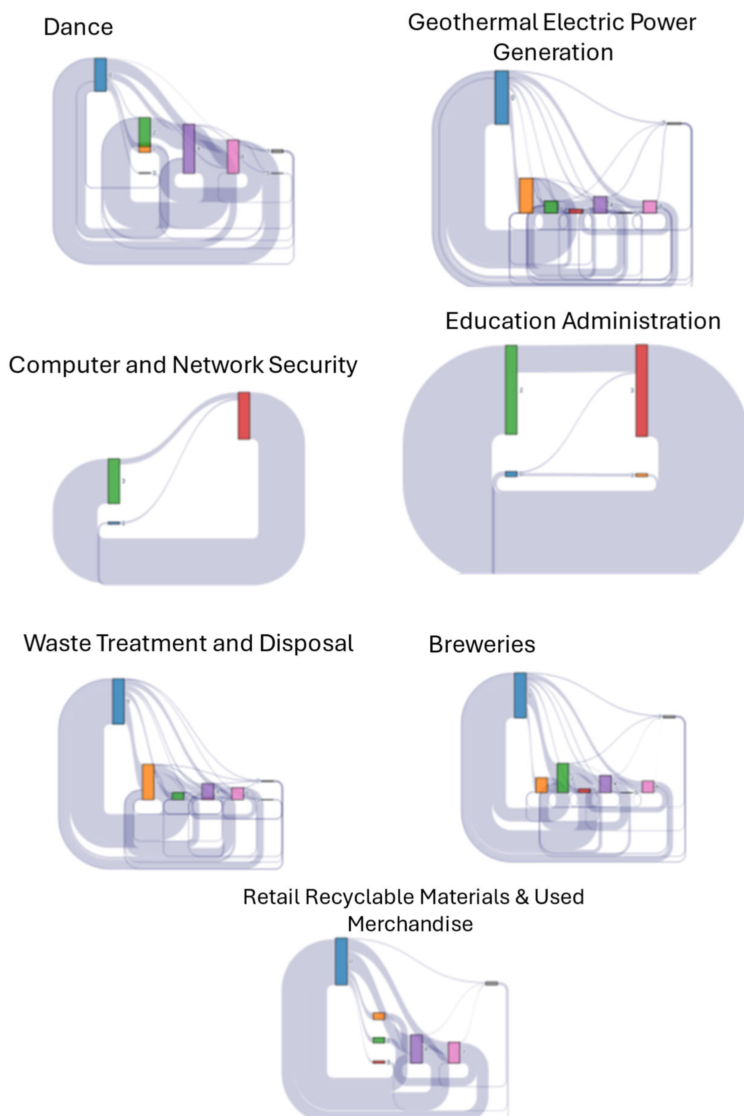
### 7.3 Strategic Importance of Demographic Differences

Professional demographic segmentation plays a central role in digital advertising, particularly on platforms like LinkedIn where industry and company size are foundational targeting criteria [7,10]. Our findings reinforce that demographic factors are not just useful for ad delivery: they fundamentally shape how users progress through the funnel.

Industries exhibited marked differences in user engagement patterns. Sectors such as retail, technology, and sports displayed higher user movement across funnel stages, with large volumes of transitions from shallow to deeper stages such as conversions and company page clicks. These industries are characterized by shorter sales cycles and more agile buying behaviors, making them highly responsive to marketing interventions. In contrast, industries like religious institutions and services for the elderly and disabled had roughly have the velocity of all other industries. These patterns are likely influenced by longer decision cycles, regulatory barriers, and complex procurement processes that dampen user responsiveness. A slower velocity is not necessarily a negative but reflects industry-specific differences.

From a campaign management perspective, these insights suggest that a one-size-fits-all strategy is likely to underperform. Advertisers targeting high-mobility industries may benefit from dynamic, multi-touch campaigns that guide users from awareness to action quickly. Campaigns in slower-moving sectors may require longer exposure windows, heavier branding investment, and more educational content to nurture users across extended sales cycles.

**Fig. 7.** Sankey diagrams displaying the marketing funnels of LinkedIn profiles in the industries of Dance (a); Geothermal Electric Power Generation (b); Computer and Network Security (c); Education Administration (d); Waste Treatment and Disposal (e); Breweries (f); and Retail Recyclable Materials and Used Merchandise (g).



### 8.3 Baseline Engagement as a Strategic Signal

A consistent feature across all demographics was the presence of a sizable baseline engagement cluster—users who had exposure to ads but had less engagement either on or off platform. This stage accounted for 4% of users in the on-platform dataset. The addition of attribution data provides additional engagements and the resulting funnel adapts to focus on deeper funnel engagement. The baseline engagement cluster grows with attribution data, but only because the funnel shifts to focus on more nuanced deeper funnel outcomes.

Strategically, the baseline engagement stage should not be overlooked as merely less active. Our transition analyses showed that users in this stage often serve as an entry point to deeper engagement; particularly into high-performing clusters like Cluster 3, which represents lead generation and conversions. This suggests that baseline engagement is not necessarily the end of the funnel but a waiting zone. With targeted retargeting strategies, it may be possible to re-activate these users and usher them toward meaningful interaction. For example, industries with high percentages of users in this stage could benefit from lightweight content (e.g., short-form video, social proof, or gated

### 9.3 Engagement Pathways and Flow Efficiency

Two dominant pathways across demographics are identified: (1) a progression from lower engagement (Cluster 0) through moderate stages (Cluster 1, 4) into high-value conversion stages (Cluster 3); and (2) toward a branding-led path beginning with high content interaction (Cluster 5) moving through exploratory engagement (Cluster 4) also culminating in Cluster 3. These patterns highlight that user journeys are not strictly linear but include complex behaviors such as backtracking, looping, and stage-skipping.

The efficiency of these flows varies by industry. Sectors like retail and sports show streamlined, high-volume transitions across stages, indicating effective funnel movement. In contrast, industries such as education and healthcare exhibit weaker flows, with many users concentrated in early stages. This suggests a need for improved messaging, more relevant content, or stronger calls to action to drive progression.

Cyclical engagement patterns also emerged, reflecting loyalty. Users in deeper stages (e.g., Cluster 3) occasionally return to earlier stages (Cluster 0 or 1), potentially due to decision fatigue. Others re-enter high-engagement stages after periods of inactivity, likely triggered by renewed campaign efforts. These cycles suggest strategic opportunities for re-engagement and highlight the importance of timing outreach based on behavioral signals.

## 6 Conclusion and Future Work

We present a data-driven approach to understanding how industry and company size demographics influence engagement behavior within B2B marketing funnels. By applying unsupervised clustering to a subset of over 200 million LinkedIn advertisement interactions across millions of users, we model funnel stages based on real-world engagement patterns. Despite variations in engagement intensity and transition dynamics, we find that the overall structure of the marketing funnel remains stable across demographic groups, validating the robustness of behavioral funnel modeling in practical industrial contexts.

One of the study's key findings is that professional demographic factors significantly impact flow sizes and transition velocities within the funnel. These differences underscore the importance of tailoring campaign strategies to demographic characteristics and sales cycle expectations. We identified common behavioral pathways, including a performance-driven route from low to high engagement and a branding-first path beginning with content interaction. Notably, no-engagement stages frequently served as entry points to deeper engagement, suggesting strategic opportunities for reactivation. Additionally, cyclical transitions highlighted signs of both user loyalty and periods of lower engagement, emphasizing the importance of monitoring and responding to behavioral shifts over time.

Future research should explore more complex industry verticals by combining factors like seniority, education, or geography with industry to better understand audience behavior. The methodology could also be extended to cross-platform and B2C settings to compare funnel dynamics across platform. Incorporating monetary outcome data would help link funnel stages to revenue, while A/B testing could validate the impact of early-stage engagements on conversions, addressing attribution bias. Together, these directions build on this study's scalable, privacy-compliant framework to support more precise targeting and performance measurement in B2B marketing.

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