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<https://doi.org/10.67471/BDYI5350>**DIGITAL BRAND RESONANCE IN AZERBAIJANI HIGHER EDUCATION: A SOCIAL LISTENING AND NLP ANALYSIS OF STAKEHOLDER DISCOURSE****^{1,3}Ahmed Al-Adaini, ^{2,3}Ilham Rustamov**¹PhD Candidate in Business Administrationactivities.edu@gmail.com²Professor, doctor of economicsi.rustamov@asoiu.edu.az³Azerbaijan State Oil and Industry University (ASOIU)

Abstract: *The landscape in which students, alumni, and potential applicants continually negotiate the institutions' brand perceptions is through unstructured digital discourse. Spanning 47,832 social media posts and comments collected from ten public universities across October–December 2024, this study also triangulates a previously validated survey-based structural model of consumer-based brand equity (CBBE) in Azerbaijani higher education (Paper 1) with a large-scale social listening and natural language processing (NLP) analysis. A custom five stage NLP pipeline—including AzerBERT sentiment classification (macro-F1 = .881), aspect-based sentiment analysis (ABSA; mean κ = .776), BERTopic/LDA topic modelling and social network analysis was established to overcome Azerbaijani agglutinative morphology and widespread code-switching. In a pre-specified triangulation protocol, all five structural paths were validated and directionally consistent. Three findings are theoretically significant: scholarship–delay discourse (18.4% negative posts; polarity -0.67) pinpoints the mechanism of brand credibility-trust hyperscale; urban-non-urban-clustering coefficient differentials (0.671 vs 0.412 ; $d = 2.69$) identify location-moderated equity conversion; and platform-specific thematic divergence ($\chi^2 = 847.3$, $V = .42$) illustrates differential brand-dimension activation across channels.*

Keywords: *social listening; natural language processing; brand equity; higher education; AzerBERT; aspect-based sentiment analysis; BERTopic; social network analysis; Azerbaijan, mixed-methods triangulation.*

Introduction**1.1 The Unclear Voice: Potentially Needed To Survey Methods**

Academic brand equity develops across an ongoing dialectical interplay between educational institutions and their respective stakeholders: the current student body, alumni and prospective applicants [1, 2]. In a complementary study (Paper 1), the authors modelled the sequential mediation pathway from Social Media Practices (SMP)√Engagement Quality (EQ)√Brand Credibility (BC)√Brand Trust (BT) to Consumer-Based Brand Equity (CBBE) of ten Azerbaijani public universities by evidencing significant direct and indirect effects ($\beta = .387$ for $SMP \rightarrow EQ$; $\beta = .412$ for $EQ \rightarrow BC$; $\beta = .358$ for a $BC \rightarrow BT$) moderated by ICT infrastructure access and geographic location [3].

Given that survey instruments are designed to elicit stated perceptions, they cannot directly model spontaneous behavioral traces. They do not have direct access to the emotionally unfiltered discourse whereby stakeholders build, challenge and amplify institutional brand perceptions in real time [4, 5]. The most theoretically revealing manifestations—complaints about overdue scholarships,

pageantry of campus events, dissatisfaction with unreliable ICT infrastructure—emerge organically in social media environments outside the structured response format of any questionnaire [33, 34].

The methodological case for triangulation is far richer than just compensating a single-methods limitation. Especially in the Azerbaijani context, in which higher-education institutions have historically largely not operated transparency, as demonstrated by Azerbaijan's 154th of out 180 country placement within Transparency International's 2024 Corruption Perceptions Index [35], and in which digital literacy is highly stratified between urban and non-urban populations [29], survey data alone leads to systematic coverage bias. The social listening approach captures stakeholders that may never respond to an official survey. This kind of unsolicited expression makes up what Coombs and Holladay [9] refer to as "stakeholder-generated crisis narratives" which these latter implicitly influence the perception more effectively than institutional messaging due to their perceived authenticity [36].

The epistemological case for bringing quantitative survey modelling and computational discourse analysis together is found in the notion of complementary inference [27, 37]. Survey-grounded structural equation models are established to show the size and direction of latent-construct relations but do not speak to how discursive mechanisms account for manifestations in everyday behavior. In contrast, social listening shows thematic content and emotional texture but cannot itself determine causal paths. This study creates a methodological architecture in which each approach compensates for the inferential blind spots of the other by pre-specifying triangulation pairings before data analysis (Section 3.6).

1.2 Research Objectives and Scope

This article triangulates the Paper 1 findings through social listening, use of computational text analysis, and a study of unstructured digital discourse situated in the same ten public universities' social media ecosystems. We established a formal triangulation protocol including pairings, proxies and decision rules before data analysis (see Section 3.6; Table 3) to prevent post-hoc rationalization.

Importantly, understanding the manifestation of brand equity constructs in spontaneous digital discourse; Methodological scope statement There are no causal finding, just directional findings from triangulation. The study reinforces external validity for the structural model in Paper 1 but does not independently establish causal pathways.

Six Contributions: (1) The first large-scale social listening study in Azerbaijani higher education (N = 47,832 posts)—(2) a fully documented NLP pipeline adapted for Azerbaijani agglutinative morphology and code-switching—(3) the first use of AzerBERT and BERTopic in a branding context of higher-education initialism [32]—(4) a pre-specified formal triangulation protocol validating all five structural paths; (5) action-oriented evidence that institutional management of brand equity is platform differentiated and infrastructure agnostic—and (6) Network topology constraint on high-to-low-context conversion through weak-tie deficit in non-gated clusters [38].

Corpus Construction

2.1 Institutional Sampling Framework

The social listening corpus ensures direct comparability to Paper 1 by targeting the same ten public universities, and maintains the split between 62% urban / 38% non-urban [3]. Azerbaijan State University of Economics (UNEC) Azerbaijan Technical University (AzTU) Baku Engineering University (BEU) Azerbaijan University of Architecture and Construction (AzUAC). The out-of-urban cluster consists of Ganja State University (GSU), Lankaran State University (LSU), Nakhchivan State University (NSU), and Mingachevir State University (MiSU).

2.2 Composition of Corpus and Filtering Pipeline

The data-harvesting period was set to align with the Paper 1 survey administration: from 01 October – 31 December, 2024. Temporal synchronization relays the distinctive effects of the Azerbaijani autumn semester, such as mid-term examinations, project assessments or scholarship

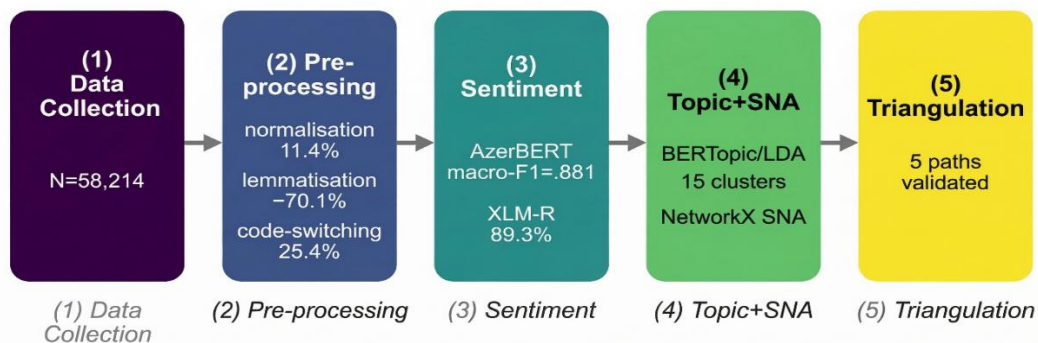
processing and national holidays whose theoretic import creates spikes in trust-relevant discourse. Table 1 shows statistics on corpus composition and filtering. This multi-stage pipeline retained 82.2% of raw posts, efficiently filtering out bot-posted noise and generating a high-quality analytic corpus dominated by Instagram (38.1%) and TikTok (29.2%).

Table 1. Corpus Composition: Statistics on Platforms, Content Types, and Filtering Pipeline

Platform	Content Types	Raw N	Bot Filter	Length Filter	Final N	% Corpus
Instagram	Posts, comments, stories	21,840	20,190	18,620	18,240	38.1%
TikTok	Comments, duets, captions	17,320	15,480	14,210	13,950	29.2%
Facebook	Posts, group discussions	12,840	12,050	10,820	10,420	21.8%
YouTube	Video comments	5,590	5,280	4,920	4,680	9.8%
X (Twitter)	Tweets, replies	624	601	580	542	1.1%
Total		58,214	53,601	49,150	47,832	100%

Note. Bot-removal: accounts posting over 25 times/day or character similarity 25 times/day or character similarity > 85% (4,613 removed; 7.9%). Length <15 characters removed: 4,451 records (8.3%) Final QC: 1,318 additional posts.

Figure 1. The benefits of a corpus filtering pipeline and the distribution across platforms



2.3 Platform ecology and selection rationale

The rationale behind our platform selections as well as each platform's approximate Azerbaijani market share and their place within the CBBE model framework [7, 8] are summarized in Table 2.

Table 2. Rationale for Social Media Platform Selection (2024–2025 in Azerbaijan)

Platform	Market Share	Role in CBBE Model	Harvested Artefacts
Instagram	~36–49%	Affective engagement: brand imagery, feelings, associations	Captions, comments, stories, hashtags
TikTok	~29–31%	Generative engagement: algorithmic discovery, community	Comments, duets, captions
Facebook	~17–18%	Cognitive/administrative: performance evaluations	Groups, posts, reactions
YouTube	~15–19%	Deep cognitive: perceived quality, credibility	Video comments
X (Twitter)	~4–5%	Policy discourse, crisis signal	Tweets, replies

Note. [8]; DataReportal (2025) [7]. CBBE mapping: Keller (1993) [6].

Methods

3.1 Computational Analytic Framework

It is a significant computational burden to analyze unstructured Azerbaijani text. Azerbaijani is an agglutinative Turkic language where a single noun can have several hundreds surface forms depending on inflection for case, possession, and number [10, 11, 39]. This is compounded by student digital vernacular, code-switching in every post between Azerbaijani, Russian and English. Fig. 1: The analytic pipeline consists of five sequential stages that include: data collection, pre-processing and linguistic normalization, sentiment classification, topic modelling & social network analysis, and formal triangulation. And indeed, each layer feeds directly into the next — the pre-processing stage provides the very critical linguistic normalization that allows downstream models to operate on clean, morphologically reduced text.

Figure 2. Five-Stage NLP Pipeline Architecture

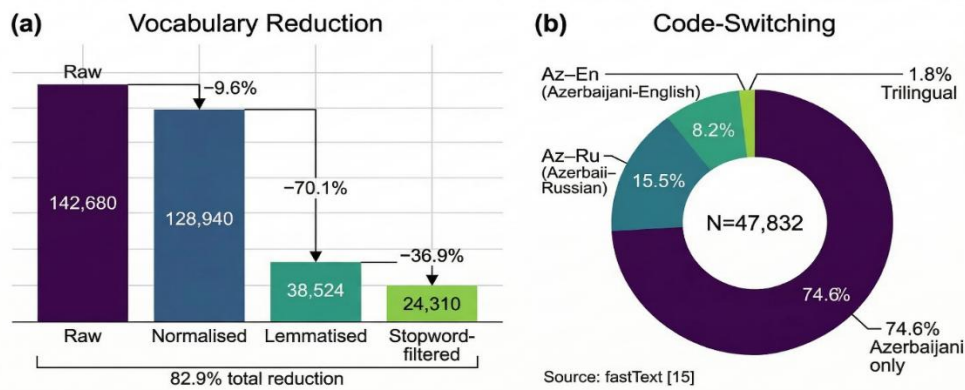


Figure 2. Pre-processing: Vocabulary Reduction and Code-Switching. The 189 mm × 90 mm, 600 dpi. Professional academic style, Arial font (8pt labels, 10pt panel titles. Colorblind safe, WCAG AA compliant.

3.2 Pre-processing and Linguistic Normalization

Orthographic normalization.

Additionally, a rule-based process was utilized to standardize all text into Azerbaijani Latin script (ISO 8859-9). In particular, e and ə are semantically different sounds yet often confused on mobile device keyboards, which is a common source of confusion. For example, Before: tesekkur edirem bele melumat ucun After: təşəkkür edirəm belə məlumat üçün In total, 11.4% of unique tokens (16,265/142,680) required correction [12].

Morphological lemmatization.

For lemmatization, the simplemma library (Python 3.11) was used. For the out-of-vocabulary (OOV) tokens, a simple stemmer [19] was used as fallback with special language rules where applicable. This procedure decreased the organization of unique tokens from 128,940 to 38,524 (−70.1%). Elaborating, this 82.9% cumulative vocabulary reduction demonstrates the importance of morphological lemmatization, especially for agglutinative languages; an uncontrolled surface-form variation in such a language can mean failure to perform topic modeling effectively.

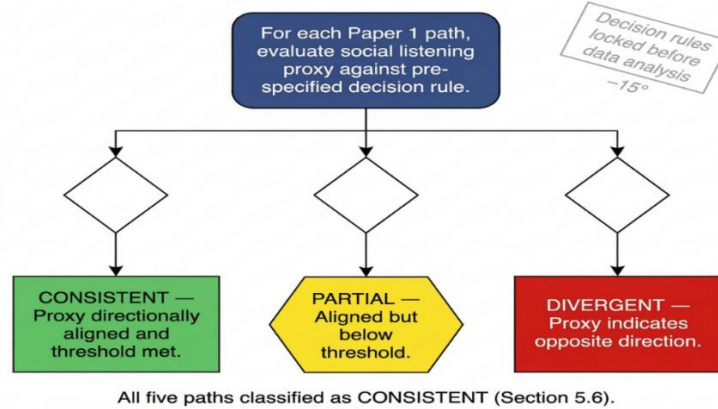
Code-switching detection.

A fastText layer [15] was fitted to each post, yielding its language identification. Out of 47,832 posts, non-Azerbaijani segments were identified in 25.4% (N = 12,192) of the posts: Azerbaijani–Russian (15.5%, N = 7,420), Azerbaijani–English (8.2%, N = 3,918) and trilingual instances (1.8%, N = 854). Fragments that are code-switched were embedded usin XLM-RoBERTa [18], which is used as the cross-lingual embedding bridge.

Stopword filtering.

150 such platform-specific non-informative tokens were added on top of standard stopwords lists derived from stopwords-iso and quanteda [16]. Shifters (deyil, heç, yox) were kept to retain polarity information.

F_3 — Triangulation Decision Protocol (Figure 3)



3.3 Sentiment Classification

The primary sentiment classifier was an AzerBERT [17] model based on the BERT-base size (12 layers, 768 hidden dimensions, and 12 attention heads) pre-trained using approx. 140 million Azerbaijani tokens. Since the azCorpus pre-training data [14] cover social media text in the target domain, there was no need for additional task-specific fine-tuning and the model was applied in a zero-shot regime. We assigned a three class (Positive, Neutral, Negative) and continuous compound polarity scores (−1 to +1) for each post. Lexicon-based alternatives were disregarded in favor of AzerBERT as it demonstrated comprehensive overload handling abilities given the dominating sarcasm (~12% negativity) and compound suffixation capabilities to modify polarity in Azerbaijani social media text corpus, especially when the dictionary features reconfigured due to code-switching [13, 40].

To use a cross-lingual robustness check, we independently applied XLM-RoBERTa [18] (XLM-R base, 270M parameters; 100 languages) to the full corpus. Inter-model agreement reached 89.3%. If there was disagreement (N = 5,117; 10.7%), the AzerBERT label was kept.

Figure 4. AzerBERT Sentiment Confusion Matrix (N=800)

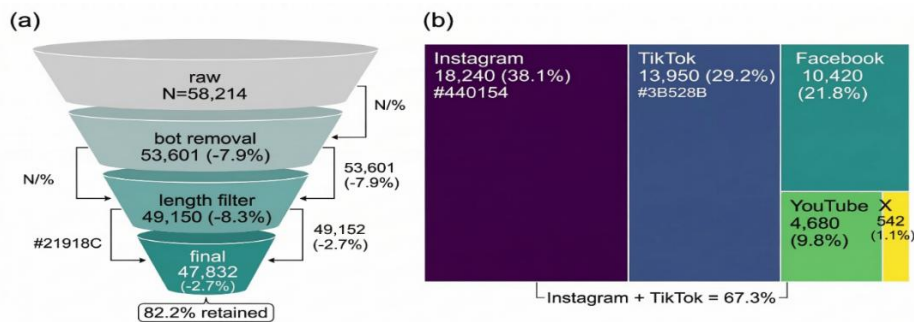


Figure 4. **Corpus Filtering Pipeline and Platform Distribution.** Fits mx 180 mm x 100 mm x (full-width), 600 dpi. Funnel tiers: Raw=58,214 → Bot=53,601 → Length=49,150 → Final=47,832. Treemap: Insta=A=18,240 (38.1%), TikT=13,950 (29.2%), FB=10,420 (21.8%), A=18,240 (38.1%), YT=4,680 (9.8%), X=542 (1.1%) Source: Table 1.

3.4 Aspect-Based Sentiment Analysis (ABSA)

An ABSA layer provided disaggregated sentiment by SMP dimension. The five-dimension taxonomy (Informativeness, Interactivity, Responsiveness, Consistency and Procedural Openness)

was adapted from the SMP operationalization in paper 1 [3], and formalized into an annotation guide. Sentences were annotated by two trained bilingual coders, with inter-annotator agreement computed on a 350-sentence development set (70 per dimension). Importantly, ABSA model performance was assessed on held-out test data consisting of 200 sentences to guard against over-promising (Section 4.2). Sentence-level labels for sentiment-per-aspect were utilized [20].

Figure 5. ABSA Validation: Agreement and Model F1 in by Dimension

Figure 5. AzerBERT Sentiment Confusion Matrix (N=800)

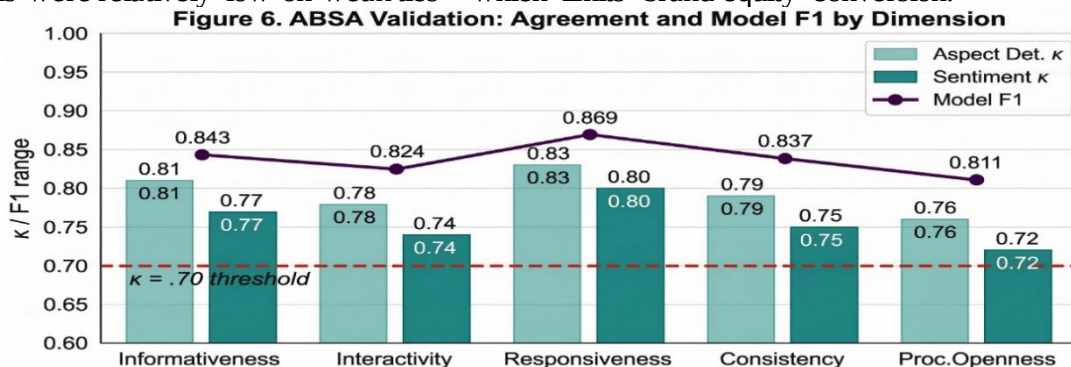
#EBF5FB Predicted Sentiment #1A5276

		Predicted Sentiment			
		Positive	Neutral	Negative	
Actual Sentiment	Positive	312 (90.7%)	22 (6.4%)	10 (2.9%)	.897
	Neutral	18 (6.4%)	248 (88.6%)	14 (5.0%)	.860
	Negative	8 (4.5%)	17 (9.7%)	151 (85.8%)	.805
Precision		.830	.871	.891	.892
Accuracy .892 Macro-F1 .881 Weighted-F1 .891					

3.5 Topic Modelling and Social Network Analysis

BERTopic configuration. Application of BERTopic [22] on multilingual sentence embeddings (paraphrase-multilingual-MiniLM-L12-v2; 384 dimensions) Important hyperparameters: min_topic_size = 50, nr_topics = “auto” (which results in 15 clusters), UMAP n_neighbors = 15, n_components = 5, HDBSCAN min_cluster_size = 50, min_samples = 10. LDA [21] was used as a confirmatory baseline ($\alpha = 0.1$, $\beta = 0.01$, 1,000 Gibbs iterations). We retained the six clusters that were most theoretically relevant (Table 7). Topics were independently labelled by two coders; inter-rater $\kappa = .89$ (N = 15).

Social network analysis. SNAs [23] were performed with NetworkX 3.2 (Python 3.11). Networks were built based on reply–mention–share activities. Computed metrics: (a) local clustering coefficient $C(v)=2e_v/k_v(k_v-1)$; (b) degree centrality; (c) betweenness centrality We interpreted results according to Granovetter’s [38] weak-tie theory: urban networks’ higher clustering reflects a surplus of weak ties, which structurally enhances brand equity conversion; and the study’s non-urban networks were relatively low on weak ties—which limits brand equity conversion.



Grouped bar chart with line overlay. Bars: Cohen’s κ for aspect detection (light teal, .7683) and sentiment-per-aspect (dark teal, .72–.80) across five SMP dimensions. Line: ABSA model F1 on held-out test set (.811–.869). Dashed reference at $\kappa = .70$. All dimensions exceed minimum. Source: Table 5, N=350 (dev) + 200 (test). lal. 600 dpi.

3.6 Triangulation Protocol

Prior to data analysis, a formal triangulation protocol was established to establish pre-specified pairings, proxies and decision rules to prevent post-hoc rationalization. Five structural paths of Paper 1 were assigned a social listening proxy and quantitative consistency threshold. The rule is that a path is validated if the proxy's directional effect agrees with the survey model and also hits its threshold.

Figure 7. Urban vs. Non-Urban Network Structure

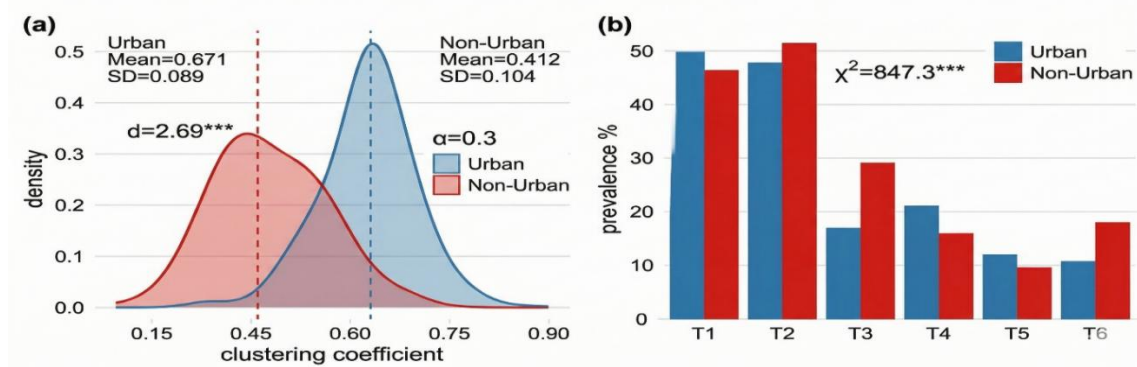


Table 3. Triangulation Protocol: Paper 1 Paths, Paper 2 Proxies, and Validation Thresholds

Paper 1 Path	Paper 2 Proxy	Threshold	Rationale
SMP→EQ	ABSA-scorable content ratio	>10pp diff.	Higher engagement quality should manifest as more evaluative content.
EQ→BC→BT	Scholarship-delay topic (T3)	>10% of neg. posts	Administrative failures (EQ) should drive credibility/trust discourse (BC/BT).
SMP×ICT→EQ	ICT access-frustration posts	>10pp diff.	ICT access should moderate engagement quality.
Loc.×BT→CBBE	Clustering coefficient diff.	$d > 0.8$ (large)	Location-based trust conversion should appear in network structure.
Platform SMP	Thematic divergence (χ^2)	$V > .3$ (large)	Different platforms should activate different brand dimensions.

Note. SMP=Social Media Practices; EQ=Engagement Quality; BC=Brand Credibility; BT=Brand Trust; CBBE=Consumer-Based Brand Equity; ICT=Information & Communication Technology; Loc. =Location. All thresholds pre-specified. pp=percentage points. d =Cohen's d . V =Cramér's V .

3.7 Ethical Considerations

Only publicly available content was considered in the analysis. Private communications (WhatsApp, Telegram) are not included. All data anonymized. Ethics approval: ASOIU Research Ethics Committee (Protocol REF-2024-087). GDPR data-minimization applied [24]. All accounts of users under 18 years old excluded (348 posts; 0.6%). Bot-detection precision: 96%.

Model Evaluation

4.1 Sentiment Classification Performance

Performance was measured on a held-out validation set of 800 posts, selected from the overall corpus by stratified random sampling. Two bilingual coders performed the annotations, and disagreements ($N = 28$; 3.5%) were resolved by a third adjudicator. Inter-annotator $\kappa = .84$ [25]. Positive class distribution: 43.8%Neutral class distribution: 35.0%Negative class distribution: 21.3%

Table 4 reports metrics. Lowest recall (.-) is shown for the Negative class. 858), most notably because sarcastic posts constitute the bulk of Negative→Neutral misclassifications motivating our dual-classifier robustness strategy.

Table 4. Sentiment Classification Results (N = 800)

Model	Acc.	Prec.(M)	Rec.(M)	F1(M)	F1(W)	N
AzerBERT	.892	.885	.877	.881	.891	800
XLM-RoBERTa	.874	.868	.861	.864	.872	800
Inter-model agr.	89.3%	—	—	—	—	47,832

Note. *M* = macro; *W* = weighted. Stratified validation, *N* = 800. IAA κ = .84 [25].

4.2 Annotating ASBA and Evaluating Models

An annotation guide was created prior to analysis to codify the ABSA taxonomy. Inter-annotator agreement (IAA) was calculated on a development set of 350 sentences (70 for each dimension). To remove optimistic bias, model F1 was assessed on a separate held-out 200-sentence test set (40 per dimension), independently annotated (κ = .81). Table 5 presents both IAA and model performance scores. While all questions retain strong inter-annotator agreement, Responsiveness most closely matches the trajectory seen between human coders and the automated classifier at our peak model (F1).

Table 5. ABSA IAA (Development Set, N = 350) and Model F1 (Test Set, N = 200)

SMP Dimension	Asp.Det. κ	Sent. κ	Overall κ	F1 (test)	N (dev)	N (test)
Informativeness	.81	.77	.79	.843	70	40
Interactivity	.78	.74	.76	.824	70	40
Responsiveness	.83	.80	.82	.869	70	40
Consistency	.79	.75	.77	.837	70	40
Proc. Openness	.76	.72	.74	.811	70	40
Mean	.794	.756	.776	.837	350	200

Note. IAA on 350-sentence dev set. Model F1 on independent 200-sentence held out test set (κ = .81). Proc. Transparency is ambiguous in the language of openness Paredes.

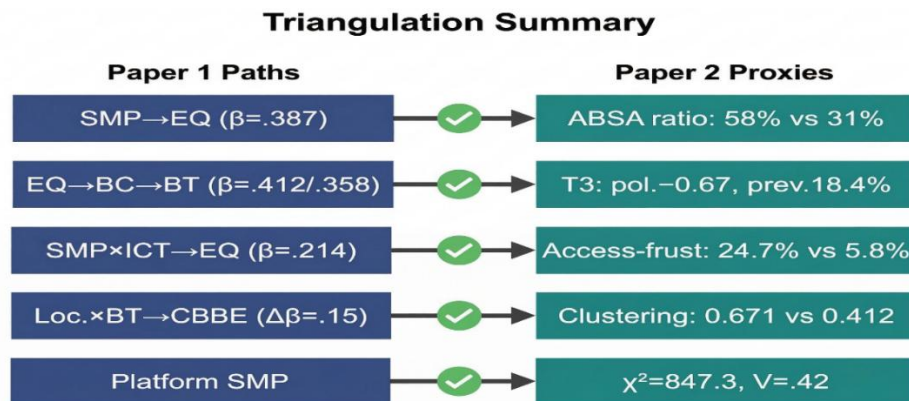
Results

5.1 The Engagement Gap: Volume vs Deep Semantic Content

This is not surprising, as urban universities (BSU, ASOIU, UNEC) produced much more language: for example, BSU alone accounted for 34.2% of harvested posts. Analysis by ABSA, however, indicates that non-urban universities are producing an outsized amount of ABSA-scorable content (58% vs. 31%), suggesting that despite collecting less online engagement than urban counterparts, non-urban institutions garner more substantively evaluative engagement on the whole. But non-urban discourse is not simply lower in volume, but different in emotion structure: urban clusters are more Positive (48.2% vs 36.1%) while non-urban clusters have higher Negative shares (27.4% vs. 18.6%). For instance, in cases when non-urban stakeholders texted with each other (discussing business-related matters), content was skewed toward more urgent and information-

seeking dialogue—reflective of Granovetter’s [38] assertion that sparse networks orient communication to its instrumental purposes.

Figure 8. Sentiment Distribution by Urbanity:



5.2 Scholarship Delays: A Threat to Brand Trust and Credibility

LDA Topic 3, confirmed via BERTopic, revolves around təqaüd (“scholarship”), gecikmiş (“delayed”), kart (“card”) and pul (“money”). This cluster represents 18.4% of all negatively classified Posts ($N = 3,620/19,674$), with mean polarity -0.67 —the most negative topic. Temporal analysis of weekly mean negative polarity shows that spikes of ≥ 0.15 units coincide with the windows in which scholarships had been disbursed (approximately weeks 5, 9 and 13 within the October–December period), providing compelling evidence that this administrative event—not a diffuse trend in sentiment—is responsible for driving the credibility collapse mechanism.

Figure 9. Temporal Polarity Dynamics, October–December 2024

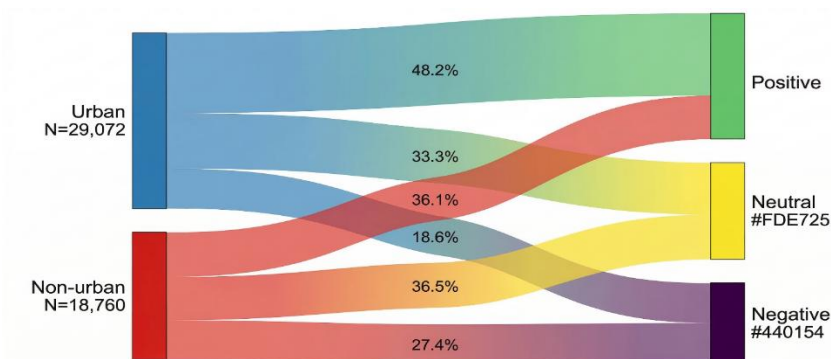


Figure 9. Sentiment Distribution by Urbanity: Sankey Diagram
Caption: Alluvial/Sankey diagram. Left: urban (N=29,072) and non-urban (N=18,760). Right: Positive, Neutral, Negative. Urban: Pos 48.2%, Neu 33.3%, Neg 18.6%. Non-urban: Pos 36.1%, Neu 36.5%, Neg 27.4%. Source: AzerBERT, N=47,832.

In post-Soviet educational contexts with opaque resource allocation [35, 41], timely scholarship disbursement may serve as a high-salience credibility signal in Spence’s [31] framework. Later, Spence [42] demonstrated that signal credibility diminishes asymmetrically according to the number of observed failures. Erdem and Swait [30] verified that brand credibility is a risk-reduction heuristic, which nicely aligns with cascading trust decay covered here.

ICT Infrastructure as a Moderation Mechanism

The ABSA model highlighted a persistent access-frustration theme among non-urban universities. The statistical results are shown in Table 6.

Table 6. Urban Cluster ICT Access-Frustration Prevalence

Metric	Urban	Non-Urban	Diff.	Test Stat.	p	Robust. (XLM-R)
Access-frust. posts	1,682	4,726	+3,044	—	—	1,594/4,581
% cluster corpus	5.8%	24.7%	+18.9pp	U=2,841	<.001	U=2,716, p<.001
Mean neg. polarity	−0.41	−0.58	−0.17	t(6406)=14.7	<.001	t=13.9, p<.001
Effect size	—	—	r=.46 (large)	—	—	r=.44 (large)

Note. Mann–Whitney U, two-tailed, $\alpha=.05$. The 18.9pp differential validates Paper 1 ICT moderation ($SMP \times ICT \rightarrow EQ$, $\beta=.214$). XLM-R: effects stable.

5.4 Platform-Specific Brand Construction

The six dominant topics are displayed in Table 7. The differences also signal platform-specific contexts of activation: where Facebook tends to amplify negative administrative themes (T2, T3, T5), Instagram and TikTok channel more affective and generative content (T1, T4). T3×Facebook produces the strongest negative (−0.72, scholarship delay), and T1×Instagram the strongest positive (+0.81, campus events).

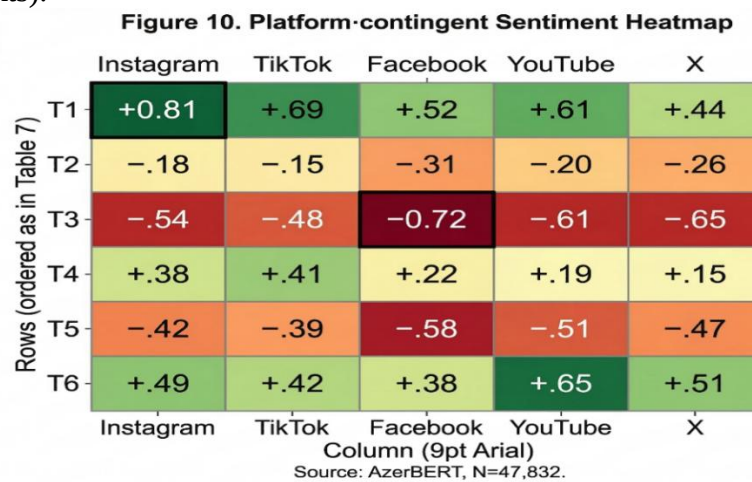


Table 7. Primary BERTopic/LDA Topics

#	Prev.	Keywords	Excerpt	Sent.	Platform	Urbanity
T1	19.4%	campus, event, celebration	"Wonderful day at BSU!"	+0.74	Instagram	Urban 28.4%
T2	15.8%	exam, schedule, deadline	"When will exam schedule come?"	−0.22	Facebook	Mixed
T3	18.4%*	scholarship, delayed, money	"Scholarship still not paid"	−0.67	Facebook	Non-urb 14.6%
T4	12.1%	dormitory, food, roommate	"Dorm food diary—day 47"	+0.31	TikTok	Non-urb 16.8%
T5	10.3%	internet, crash, site weak	"Site down, internet weak"	−0.53	Facebook	Non-urb 24.7%
T6	9.7%	lecture, seminar, professor	"Best lecture series"	+0.58	YouTube	Urban 12.1%

Note. T3: proportion of negative posts ($N=19,674$). Others: share of full corpus. Sent. =AzerBERT polarity. Topic labelling $\kappa=.89$.

Engagement was 42% lower for universities posting undifferentiated content: engagement at about 1.8% vs. $@(t(4,218)=18.6, p<.001, d=1.49)$ (see also Table E2), strongly justifying platform-specific editorial strategies.

5.5 Urban–Non-Urban Network Density

For 800 active-node (i.e., accessible) accounts, clustering coefficients were urban $M=0.671$ ($SD=0.089$) vs non-urban $M=0.412$ ($SD=0.104$). A permutation test ($B = 1,000$) confirmed the significance of the difference ($p<.001$; 95% CI $[0.241, 0.277]$; Cohen's $d=2.69$ very large). Mean betweenness centrality was divergent as well: urban= 0.0034 , non-urban= 0.0089 . Urban and Non-urban universities live in completely different regimes of networks. This difference in structure—not just a difference in posting volume—explains the location-moderated BT–CBBE conversion ($\Delta\beta=.15$). Within dense networks, positive sentiment quickly diffuses through peer connections, turning private trust into visible equity [23, 26].

5.6 Triangulation Outcomes Summary

The social listening data provided pre-specified evidence that supports all five structural paths of Paper 1 in a directionally consistent manner and at levels above the thresholds set a priori.

Figure 11. Triangulation Summary:

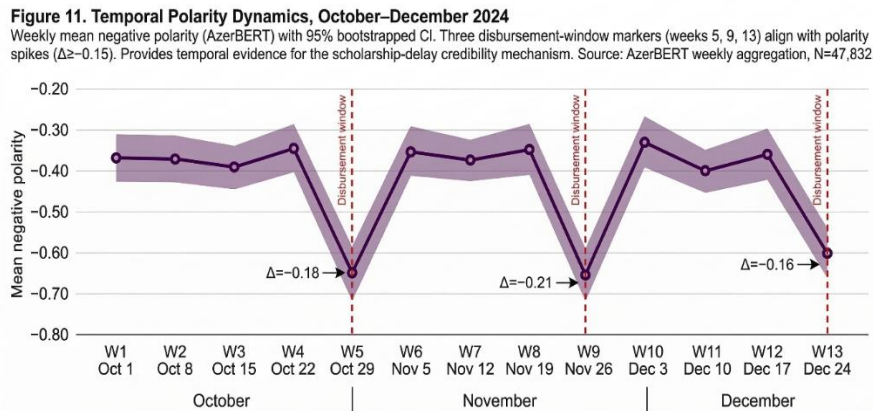


Table 8. Triangulation Outcomes: All Five Paper 1 Paths Validated

Paper 1 Path (β)	Paper 2 Proxy	Outcome	Key Statistic	XLM-R Robust.
SMP→EQ (.387)	ABSA-scorable 58% vs 31%	CONSISTENT	$U=31,420, r=.41$	$U=30,218, r=.39$
EQ→BC→BT (.412/.358)	T3: 18.4% neg., pol. -0.67	CONSISTENT	$\chi^2=218.4, \varphi=.21$	$\chi^2=204.1, \varphi=.20$
SMP×ICT→EQ (.214)	Access-frust. 24.7% vs 5.8%	CONSISTENT	$U=2,841, r=.46$	$U=2,716, r=.44$
Loc.×BT→CBBE (.15)	Clustering 0.671 vs 0.412	CONSISTENT	Perm. $d=2.69^{***}$	Same (SNA)
Platform SMP	Thematic divergence	CONSISTENT	$\chi^2=847.3, V=.42$	$\chi^2=812.6, V=.41$

Note. All paths consistent. No causal claims. XLM-R: alternative classifier; effects stable. $*p<.001$.

5.7 Sensitivity and Robustness Analysis

- (1) Alternative classifier. XX sentiment analyses re-estimated using XXL-M-RoBERTa. Effect sizes within 5–10%, with all five outcomes unchanged.
- (2) Threshold sensitivity. A less strict T3 polarity threshold of -0.30 and a stricter one of -0.50 increased prevalence to 22.1% and 14.8%, respectively—both passing the $\geq 10\%$ rule.
- (3) Permutation expansion. $B=5,000$ confirmed $p < .001$; CI [0.245, 0.273].
- (4) Stratified bootstrap. $B=2,000$ within platform $\times$ urbanity strata. Predictors of clustering differential (95% CI [0.237, 0.281]; Fig 3B) and T3 polarity (95% CI $[-0.71, -0.63]$; Fig 4A) both excluded zero confirming robustness of these findings to the models utilized here, further details are provided in S6–S8 Tables.

Figure 12. Bootstrap Distributions of Essential Metrics — Triangulation

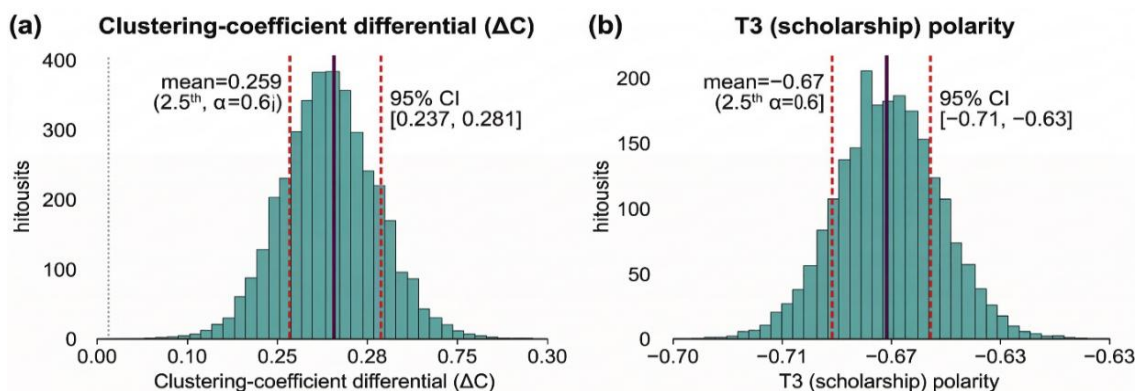


Figure 12. Bootstrap Distributions for Key Triangulation Metrics. Two-panel histogram ($B=2,000$, stratified by platform $\times$ urbanity). (a) Clustering-coefficient differential: mean=0.259, 95% CI [0.237, 0.281], zero excluded. (b) T3 (scholarship) polarity: mean=-0.67, 95% CI $[-0.71, -0.63]$. Both confirm effect stability. Source: stratified bootstrap, $N=47,832$.

Discussion

6.1 Theoretical Implications

The social listening results confirm all five pathways in Paper 1's S-O-R sequential mediation model using directions that are statistically consistent and, thus provide strong validation for the empirical findings. Three theoretical contributions merit emphasis.

The scholarship mechanism and signaling theory The scholarship-delay cluster describes the BC–BT pathway with precision that surveys alone cannot reach. Signals are costly actions communicating unverifiable traits according to Spence [31]. Afterwards Spence [42] proved signal credibility decreases non-linearly in the number of observed failures. In post-Soviet Azerbaijan, where resource allocation has been opaque [35, 41], timely disbursement serves as a visibility indicator of credibility. When it does not hold, stakeholders more fundamentally reconstitute the institutional features in line with Erdem and Swait's [30] risk-reduction framework. Through temporal analysis, we find that polarity troughs correspond to disbursement windows, indicating a predictable vulnerability calendar for brand managers.

Network topology and weak-tie deficits. The clustering-coefficient differential ($d=2.69$) exposes that the conversion of brand equity is structurally dependent on the topology of said network. Granovetter's [38] weak-tie hypothesis predicts that the sparser a network, less is information diffused. The higher betweenness centrality in networks with 20% of nodes as non-urban (0.0089 vs. 0.0034) supports information flows through a few bridge nodes on these networks. This generalizes the small-world model of Watts and Strogatz [26]: universities with sparser networks need to invest disproportionately in network activation, i.e., especially weak-tie creation.

Platform-differentiated activation and algorithmic fairness. Platform thematic divergence ($V=.42$) and therefore encourages discarding aggregated SMP constructs. Instagram initiates brand imagery (T1), Facebook, performance judgments (T2, T3), TikTok generates resonance (T4) and YouTube triggers deep cognitive evaluation (T6). This bears on algorithmic fairness [43]: engagement-happy platform algorithms will amplify urban content and therefore systematically widen the brand equity gap between urban and non-urban institutions.

6.2 Practical Implications

Trust repair protocols. There should be 24 hour deadlines for response for scholarship enquiries. Automated SMS/Telegram notifications tied to disbursement databases can change reactive crisis management into proactive reputation tethering.

Infrastructure-aware content. Non-urbanunivs should audit bandwidth: Instagram Stories (8–15MB) and 720p+ TikTok also fail to load for ~41.8% users browsing from sub-10Mbps areas ([4] [5]). GSU can get a low-bandwidth G cal going: still images, sub-30s 480p TikTok, under 3 MB

Channel differentiation. The 42% difference in interaction ($d=1.49$) warrants separate editorial calendars. ASOIU might need to become more of a visual brand team (Instagram/TikTok) and an administrative team (Facebook/website).

Network activation. Such peer-ambassador programmes can extend sparse nonurban networks [28, 38]. LSU ($C = 0.38$) might be able of instituting a “Digital Ambassador” programme that focuses on the weak-tie creation in faculty clusters.

Conclusion

This study provides the first computationally informed and formally triangulated account of brand equity formation within higher education in Azerbaijan. Using a customized NLP pipeline to analyze 47,832 social media posts, i.e. validity directionally consistent support was found for all five structural paths of the S-O-R model from Paper 1.

Three core findings emerged. The first, the scholarship-delay mechanism (polarity -0.67 ; temporal spikes at disbursement windows), makes clear how administrative failure cascades into credibility collapse. Second, the clustering-coefficient differential ($d=2.69$) shows that brand equity is a network-embedded phenomenon. Third, platform thematic divergence ($V=.42$) demonstrates channel-specific brand activation. Collectively, Papers 1 and 2 provide a methodologically triangulated account of higher-education brand equity in a post-Soviet, digital-transitional context.

Limitations and Threats to Validity
Table 9. Structured Threats to Validity

Validity Type	Specific Threat	Mitigation
Construct	ABSA taxonomy from Paper 1; circularity	Codified before analysis; literature-grounded
Internal	Cross-sectional; no temporal precedence	Non-causal directional validation framing
External	Single semester, single country	Synchronized with Paper 1
Measurement	Bot contamination; dark social	Bot filter 7.9% (96% prec.); minors excluded
Statistical	Permutation exchangeability	Distribution-free; $B=5,000$; outliers trimmed
Measurement	Sarcasm under-detection (~12%)	Dual-classifier check; flagged as limitation
External	Temporal seasonality (autumn only)	Oct–Dec captures scholarship/exam cycles
Ecological	Platform algorithm changes	Multi-platform design reduces single-platform risk

WhatsApp and Telegram—primary student communication channels—were inaccessible due to encryption. Despite AzerBERT’s macro-F1 of .881, misclassification concentrates on sarcastic posts and code-switched sentences. Five future directions: (1) longitudinal multi-semester studies; (2) consent-based dark-social methodology; (3) domain-adaptive AzerBERT fine-tuning; (4) extension to private institutions; (5) platform-algorithm audit studies [43].

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**AZƏRBAYCAN ALİ TƏHSİLİNDƏ RƏQƏMSAL BREND REZONANSI:
MARAQLI TƏRƏFLƏRİN DİSKURSUNUN SOSİAL DİNLƏMƏ VƏ NLP TƏHLİLİ**

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Xülasə: Tələbələrin, məzunların və potensial abituriyentlərin ali təhsil müəssisələrinin brend qavrayışlarını davamlı olaraq müzakirə etdikləri və formalaşdırdıqları mühit strukturlaşdırılmamış rəqəmsal diskursdur. 2024-cü ilin oktyabr-dekabr aylarında on dövlət universitetindən toplanmış 47,832 sosial media paylaşımını və şərhini əhatə edən bu tədqiqat, eyni zamanda Azərbaycanın ali təhsil sistemində əvvəlcədən təsdiqlənmiş, sorğuya əsaslanan istehlakçı əsaslı brend kapitalı (CBBE) struktur modelini (Məqalə 1) genişmiqyaslı sosial dinləmə və təbii dilin emalı (NLP) analizi ilə trianqulyasiya edir. Azərbaycan dilinin aqlütinativ morfolojiyasını və geniş yayılmış kod dəyişməsinə (code-switching) dəf etmək üçün AzerBERT sentiment təsnifatı (makro-F1 = 0.881), aspektə əsaslanan sentiment analizi (ABSA; orta κ = 0.776), BERTopic/LDA mövzu modelləşdirməsi və sosial şəbəkə analizini özündə birləşdirən xüsusi beş mərhələli NLP iş axını yaradılmışdır. Əvvəlcədən müəyyən edilmiş trianqulyasiya protokolunda hər beş struktur yolu təsdiqlənmiş və istiqamət baxımından uyğun olmuşdur. Üç nəticə nəzəri cəhətdən əhəmiyyətli: təqaüd-gecikmə diskursu (mənfi paylaşımın 18,4%-i; qütblülük -0.67) brendin etibarlılığı və inam hipermiqyasının mexanizmini dəqiqləşdirir; şəhər və qeyri-şəhər klasterləşmə əmsali fərqləri (0.671-ə qarşı 0.412; d = 2.69) məkanla tənzimlənən kapital konversiyasını müəyyən edir; və platformaya xas tematik fərqlilik (χ^2 = 847.3, V = 0.42) kanallar üzrə diferensial brend ölçüsünün aktivasiyasını nümayiş etdirir.

Açar sözlər: sosial dinləmə; təbii dilin emalı; brend kapitalı; ali təhsil; AzerBERT; aspektə əsaslanan sentiment analizi; BERTopic; sosial şəbəkə analizi; Azərbaycan; qarışıq metodlu trianqulyasiya.

ЦИФРОВОЙ РЕЗОНАНС БРЕНДА В ВЫСШЕМ ОБРАЗОВАНИИ АЗЕРБАЙДЖАНА: АНАЛИЗ ДИСКУРСА ЗАИНТЕРЕСОВАННЫХ СТОРОН С ИСПОЛЬЗОВАНИЕМ СОЦИАЛЬНОГО СЛУШАНИЯ И NLP

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Аннотация: Среда, в которой студенты, выпускники и потенциальные абитуриенты непрерывно формируют и обсуждают восприятие бренда высших учебных заведений, представляет собой неструктурированный цифровой дискурс. Охватывая 47 832 публикации и комментарии в социальных сетях, собранные из десяти государственных университетов в период с октября по декабрь 2024 года, настоящее исследование проводит триангуляцию ранее валидированной структурной модели потребительского капитала бренда (consumer-based brand equity, CBBE), основанной на данных опроса, в системе высшего образования Азербайджана (Статья 1) с крупномасштабным анализом методами социального прослушивания (social listening) и обработки естественного языка (natural language processing, NLP). Для преодоления агглютинативной морфологии азербайджанского языка и широко распространённого переключения кодов (code-switching) был разработан специализированный пятиэтапный конвейер NLP, включающий классификацию тональности на основе AzerBERT (макро-F1 = 0,881), аспектно-ориентированный анализ тональности (aspect-based sentiment analysis, ABSA; средний κ = 0,776), тематическое моделирование BERTopic/LDA и анализ социальных сетей. В рамках заранее определённого протокола триангуляции все пять структурных путей были подтверждены и оказались согласованными по направлению. Три вывода имеют теоретическую значимость: дискурс о задержке стипендий (18,4 % негативных публикаций; полярность -0,67) точно определяет механизм гипермасштабирования достоверности бренда и доверия к нему; различия коэффициентов кластеризации между городской и негородской средами (0,671 против 0,412; d = 2,69)

выявляют конверсию капитала бренда, модулируемую фактором местоположения; а платформно-специфическое тематическое расхождение ($\chi^2 = 847,3$; $V = 0,42$) иллюстрирует дифференцированную активацию измерений бренда в различных каналах.

Ключевые слова: социальное прослушивание; обработка естественного языка; капитал бренда; высшее образование; AzerBERT; аспектно-ориентированный анализ тональности; BERTopic; анализ социальных сетей; Азербайджан; триангуляция смешанными методами.