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A Systematic Analysis of Content Structural Efficiency for Estimating Higher Educational Institution Engagement Over Facebook

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ABSTRACT

The purpose of this research article is to examine the Facebook content themes and structural efficiency of higher education institutions in order to understand how these factors influence engagement. The sample consisted of 4,703 Facebook posts from the top ten most popular Indian and global higher education institution pages. The platform engagement options were used to categorize audience reactions, while structural attributes were examined in accordance with applicable theory using a negative binomial regression model. Factor analysis and descriptive metrics were used to evaluate theme efficacy. The findings highlight the significance of developing a comprehensive assessment of content structural efficiency. The paper presents a number of evidence-based recommendations for projecting and estimating content performance. This study adds to the body of knowledge by first merging the content subject with its structural parts. Previously, the content theme was thought to be a qualitative unit.

KEYWORDS

Audience Engagement, Audience Interest, Content Structure, Content Theme, Post Interaction

1 INTRODUCTION

Websites and social media are the most regularly used digital marketing channels (Taiminen & Karjaluoto, 2015). Digital marketing extends convenience along with marketing (Lau et. al., 2018). Social media facilitates interaction, information, word-of-mouth, customization, and trendiness (Yadav and Rahman, 2019). Social media can be utilized for a variety of purposes like awareness and real-time feedback (Al-Awadhi and Al-Daihani, 2018). Social media marketing communication had a favorable impact on attitude (Duffett, 2017). Social media has a favorable impact on a brand's functional and symbolic image (Gokerik et al., 2018). Brand loyalty, brand consciousness, and value consciousness are all positively influenced by social media marketing (Ismail, 2017). Social media exposure has a great impact on buying (Karen et al., 2017). Brand image and reputation are significantly impacted by social media (Godey et al., 2016; Seo and Park, 2018).

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Napoleoncat reported (Facebook users in India, 2021) India has approximately 450 million Facebook users in August, 2021. Comparing reports for January and August, 2021 shows an increase of 14.5% user within 7 months and the user base between the ages 25-34 grew by almost 10%. Facebook's global user base grows at a yearly pace of 12% (Newberry, 2021) whereas it grows at a rate of 12-13% in India (Statista, 2021). Approximately, 23.8 percent of Facebook users are between the ages of 18 and 24, while 82 percent of college graduates are on Facebook globally (Aslam, 2021). Higher education has remained among the top ten social media-using industries for the past five years, with 6.8 posts per week (Feehan, 2021). Higher education has the third highest average engagement per post on Facebook internationally; Higher education in India is thriving and according to a forecast from brandequity (2021), digital ad expenditure across all sectors will increase by 65 percent. Higher education institutions had lower rates of engagement on Facebook in 2018 than in 2017, and this has become a Year-on-Year (YoY) phenomenon. The reported global average for Facebook interaction per post across all industries is roughly 3.28 percent, but higher education was obtained at 0.12 percent in 2019 (Feehan, 2019), which is significantly lower than the average rate. Higher education has a lower interaction rate with lower spending per click on Facebook than the global average (Irvine, 2019).

2 LITERATURE REVIEW

There is a lot of information available in the business section of the Facebook website on success stories of educational institutions implementing Facebook for lead generation and conversion in their depository. The world average engagement rate for Facebook post is 0.18% (Newberry, 2021) while average engagement rate for higher educational pages was 0.14% (Feehan, 2021) and 0.16% under low performing category (Jipa, 2021). Feehan (2021) in the report on higher education for RivalIQ (2021) obtained 0.65% average engagement for top 10 most performing higher educational institution pages, but the highest engagement rate obtained by an individual unit was just 1% (University of Iowa). It also mentioned the average engagement rate for colleges and universities declined by 20% in 2021. The marketing success cases available at the Facebook depository for higher education are not directly linked with content engagement rather it's more of deep learning of target marketing. If Feehan 2019 and 2021 reports are to be compared, the average engagement rate for higher education increased by 0.02% over three years. The engagement rate has been defined as the total engagement divided by the number of followers in the aforementioned studies. That means an increase in community size can further dilute the engagement rate. Hence this study proposes to design a model to estimate engagement based on content structure.

2.1 Determining Engagement Measure

Researchers have used platform interaction attributes to measure content flow. Interaction KPIs and metrics are significant factors for social media activity evaluation (Keegan and Rowley, 2017). Earlier researchers have studied the Facebook interactions such as: share, like, comment and reaction. They have defined these interactions as recommendation, endorsement, conversation and expression (Hennig-Thurau et al., 2004; Hennig-Thurau et al., 2010; Swani et al., 2013; Dhaoui, 2014; Alboqami et al., 2015; Liu et al., 2017). Moran et al. (2019) and Tafesse (2015) have mentioned the requirement of accessing engagement in terms of interaction. Target interaction can be defined as the interaction option of a platform that a post intends to target for engagement. As this study is about Facebook the above mentioned interactions has been used for evaluating engagement.

2.2 Content Theme (CoTh)

The study intends to categorize contents published by higher education institutions' on Facebook by 'Theme' and identify the best content structure for performance (engagement). There are few distinguishable characteristics; vividness and novelty (Tefesse, 2015) and interaction cue (Moran et al., 2019). However, this study assumes that CoTh is independent of any structure, implying that the content structure is always built around a specific theme. The overall content structure has been depicted in Figure 1. Specific contents allow pages to stay in touch with the community (Lipsman et al., 2012). It is more important to focus on content rather than the channel (Kelsey & Lyon, 2017, p. 51). Interactive contents with instructive elements are most engaging and informative contents act as engagement driver (Alboqami et al., 2015). Entertainment and interaction are some aspects of social media posting (Kim and Ko, 2010). The entertaining, emotional, and interesting contents highly influence social media engagement (Barger et al., 2016). Different posts have varying effects on engagement (Tsimonis and Dimitriadis, 2014; Cawsey and Rowley, 2016). Interactive posts and mix appeal receives the highest interaction on Facebook (Kusumasondjaja, 2018). Entertainment is a powerful engagement driver (Park et al., 2009; Muntinga et al., 2011). Puto and Wells (1984) suggested a two-dimensional categorization model that was based on transformation and information appeal, which was again suggested by Laskey et al. (1989). The researchers have concentrated heavily on broad categories; however, these categories are still made up of multiple sub-categories of content message call theme. Tafesse and Wien (2017) proposed a framework of twelve brand post categories depending on message design. Previous research has provided significant knowledge on the importance of content appeal but has not clearly demonstrated a method for analyzing the impact of CoTh on overall engagement.

2.3 Content Theme Measurement

The need for CoTh quantification in this study is eminent, as considering it a qualitative unit would not generate estimates for the proposed structural effectiveness model. The impact of social media community interaction over the brand image, loyalty, purchase decision, engagement development, and satisfaction has been studied and established by many earlier researches (Ramanathan et al., 2017; Pongpaew et. al., 2017; Vorah and Bhardwaj, 2019; Rossmann et al., 2015; Gruen et al., 2006; Shareef et al., 2019). Other sets of studies defined different levels of community participation over social media like; consumption, contribution, and creation (Muntinga et al., 2011; Tsai & Men 2013; Shareef et al., 2019). These studies helped in understanding the relevance of community participation towards engagement development. Hence, this study proposed to quantify the CoTh in terms of community interaction. The quantification of CoTh has been done based on metrics that can be processed with publicly available data. Keegan & Rowley's (2017) suggested metrics for evaluation should be decided based on need and possible processing. Peters et al. (2013) illustrated the importance of content measurability and network influence. As such, this study proposes two metrics: 'post interaction ratio' (PI) and 'contribution ratio' (C_{ont}) for measuring theme worth.

RQ-1. What is the most engagement effective *CoTh* based on PI and C_{ont} for higher educational institutions?

2.4 Content Structure

a. Content Type (CoTy)

According to the platform's specifications, content on Facebook follows a set format: video, album, image, text, and story. Posts with high degree of representation have a positive impact on performance (Kaplan & Haenlein, 2010). Sensory properties are influenced by post-structural factors (Fortin & Dholakia, 2005). Tafesse (2015) discussed the positive effect of post vividness (type) on audience reaction. Online content with a variety of features, such as an image and text, might provide higher-order appeal (Daugherty et al., 2008). Facebook posts with multiple structural aspects have a beneficial impact on audience response (Sabate et al., 2014). The influence of video is higher than any other format as per the Facebook website. Facebook believes content type is a major signal for content placement (Cooper, 2021). We propose 'Post Type' categories as Text, Link, Image, Album and Video.

b. Perceived Action (PA)

The theoretical knowledge of the impact of interaction on post-engagement is divided into two halves. Some says that brand post interactivity boosts overall engagement (de Vries et al., 2012; Sundar & Limperos, 2013; Moran et al., 2019) while others say that interactivity has a negative impact on engagement (Fortin & Dholakia, 2005; Hanna et al., 2011; Tafesse, 2015). Interactivity can have three effects on post engagement: good, negative, and neutral (Liu, 2003; Fortin & Dholakia, 2005). However, interaction has an impact on post-engagement in either direction. Interactivity is classified into three degrees based on complexity: low, moderate, and high (de Vries et al. 2012; Tefesse, 2015; Moran et al., 2019). We propose 'Perceived Action' categories as Interaction, Participation, Subscribe and Conversion.

c. User Involvement (UI)

The way content appeals to the user for interaction have been theoretically considered as involvement. User interaction influences content engagement (Moran et al., 2019; Sabate et al., 2014; Schmidt et al., 2008; Tefesse, 2015). One sort of involvement is content consumption (Calder & Malthouse, 2008, p. 253). Different types of content necessitate varying levels of user engagement. For example, an image (with or without interaction appeal) can be consumed with a simple view, whereas an online workshop or an article necessitates a higher level of involvement. Hence, the proposed factor is User Involvement whose overall structure has been built with primary data as no literature is available to define the elements. We propose 'User Involvement' categories as View, Read, Passive Participation and Active Participation.

d. Target Audience (TA)

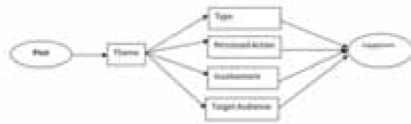
Target audience in the context of content analysis has received little attention from researchers and theoretical information for target audience is not readily available. However, Facebook offers ample functionalities for customizing audience targeting. As a result, the target audience becomes an important part of the engagement. Several studies emphasize the relevance of the target audience for engagement based on real time data from social media marketing platforms (Newberry, 2019; Forsey, 2021; Zote, 2021). Since, the level of information required to fully implementing the target audience as an aspect of content structure is limited; the content appeal to a certain segment of the audience has been used as the categorization criterion in this study. We propose 'Target Audience' categories as Internal, External and Not Specified.

RQ 2: What is the most effective content structure for higher education institutions?

2.3.1 Proposed Content Structural Efficiency Model

The structural efficiency model is prepared with available theoretical literature on content structural models and its applicability has been demonstrated in this study.

Figure 1. Content Structural Efficiency Model



We propose 'CoTh', 'CoTy', 'PA', 'UI', and 'TA' as elements of the overall content structure. The model to estimate structural efficiency is illustrated in figure 1. This study considers the theme to be independent of structure and dependent on 'target interaction'. Thus, once the page decides the specific interaction it aspires to target with a post; it requires estimating the most contributing theme and adjusting the structure accordingly. The following hypotheses have been formulated based on the literature review to support the significance of structural elements per 'target interaction'.

$H_0 2_{ij}$: Post type has no significant impact on Interaction
$H_0 3_{ij}$: Perceived Action has no significant impact on Interaction
$H_0 4_{ij}$: User Involvement has no significant impact on Interaction
$H_0 5_{ij}$: Target Audience has no significant impact on interaction

where 'i' is type element and 'j' is interaction.

Based on the research questions 1 and 2, the objective of this study is to *Identify most effective content structure for higher education institutions' Facebook engagement performance.*

3 METHODOLOGY

The analysis is divided into two parts: global (G) and Indian (Ind). The analysis was carried out in order to reach a conclusion about the comparative scenario of both sample groups.

3.1 Sampling

For determining the pages, the community size of a Facebook page as of January 1, 2021 was used. All the posts made between January 2021 and May 2021 by the top ten higher educational institutions' Facebook pages (both global and Indian) were extracted. Figure 2 and 3 illustrates the base samples for data extraction.

Figure 2. Indian Sample

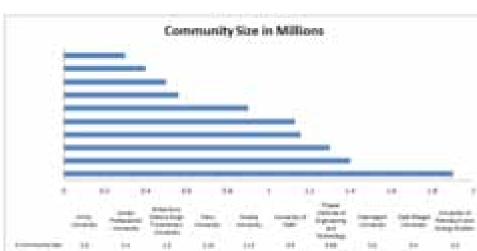
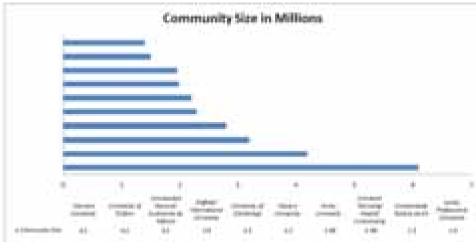


Figure 3. Global Sample



3.2 Data Collection

The content Meta description per post and related interaction elements have been extracted using the online data extraction tool, Fanpage Karma on May 15, 2021.

3.3 Proposed Model for Analyzing CoTh Performance

The research analytical model is divided into two parts: content theme effectiveness (RQ-1) and content structural efficiency (RQ-2).

3.3.1 Content Theme Effectiveness (RQ1)

The proposed model for CoTh effectiveness is based on the effective interest of the audience; the most successful content theme combination was determined using the Adjusted R^2 value achieved through step-wise multiple logistic regressions. The content theme mix was created using a structural equation modeling approach. The audience interest was determined using the 'post-interaction ratio' (PI). The PI equation, i.e., the ratio of effective interest was created using Munoz et al. (2017) and contribution value calculation is based on the relative measure concept suggested by Barman (2020). The following equation determined PI values:

$$PI_j = \frac{Engagement}{Exposure} \text{-------------------------} \quad (1)$$

where, 'PI_j' is the PI for post j

The resulting PI values were used in factor analysis to determine the base model for the theme mix. Furthermore, the model mix is analyzed with step-wise multiple regressions considering 'post exposure' as an independent variable (X) against the dependent variable, 'engagement' (Y). All the themes obtained from the factor analysis were considered as a base model for the regression analysis and low contribution themes were removed with every successive rotation until adjusted R^2 fell below the base model. The data set extracted for this study was observed to be non-normal, hence the study employs log-log transformation regression (Benoit, 2011), as explained below:

$$log(Y_{ej}) = \alpha_e + \{\text{å}\beta_1\, log(PE_{j1}) + \beta_2\, log(PE_{j2}) + \ldots\ldots\ldots + \beta_n\, log(PE_{jn})\} + \varepsilon_i \text{-------} \quad (2)$$

Where $log(Y_{ej})$ indicates the log of engagement (e) for posts 1, 2, 3, and so on. β_1, β_2, β_3, β_4, β_n indicates the regression coefficient for $log(PE_{tn})$, and $log(PE_{t1})$ represents the post exposure for post j=1,2,3,4, and so on. Based on the Adjusted R^2 value derived from the regression analysis, the best performing content mix has been estimated. The theme contribution was obtained with the following equation:

$$\text{Content Contribution } (C_{ont}) = \frac{Theme \;\; Engagemen\left(CTx\right)}{Aggregate \;\; Engagement} \text{ --------------} \qquad (3)$$

3.3.2 Content Structural Efficiency (CSE)

The structural efficiency model is based on models proposed by previous researchers (Kumar et. al., 2018; Tefesse, 2015; Moran et al., 2019). A wide number of studies have employed platform interaction options as parameters for analysis (de Vries et al., 2012). It was studied independently by verifying the statistical significance of the structural elements and their total impact on 'Target Interaction' (like, comment, share, and reaction). The model testing equation is given below. Previous research (Moran, 2019; Hilbe, 2014) recommended using the Negative Binomial model to examine the effect of factors in a count data set.

Model Equation:

$$Y_{ij} = exp\ \beta\ (å\ \beta_o + \beta_{\text{Type tj}}\ X1j + \beta_{\text{Perceived Action aj}}\ X2j + \beta_{\text{Target Audience nj}}\ X3j + \beta_{\text{Involvement zj}}\ X4j).$$

Where; Y_{ij} => Y_{1j} or Y_{2j} or Y_{3j} or Y_{4j} ; log of post like, share, comment and reaction respectively and exp β_{zi} is the equation regression coefficient obtained as parameter estimates (z = element).

3.3 Content Classification Approach

The classification of content for social media posts can be done either using an inductive or deductive approach (Anandarajan et al., 2019, p-16). Tafesse and Wien (2017) proposed a stepwise deductive-inductive categorization approach. Their framework was employed as an initial content assortment technique. Because it lacks categories that are specifically appropriate to higher educational institutions. Hence, the final list of categories was prepared using real-time data.

3.4. Content Classification Framework

Framework for this study has eight adjustments to the framework suggested by Tafesse and Wien (2017). Table I represents the content categories and adjustments.

Table 1. Content (Theme) Categories

WTafesse & Wien (2017)	Study Conceptual Framework	
Proposed categories	Result	New Proposed Name
Emotional	Retained*	Emotional*
Functional	Re-adjusted**	Institutional**
Educational	Split***	Learning*** and Informative***
Brand Resonance	Retained*	Brand Resonance*
Experiential	Retained*	Experiential*
Current event	Retained*	Current event*
Personal	Re-adjusted***	Students***
Employee	Retained*	Employee*
Brand community	Retained*	Brand community*
Customer relationship	Retained*	Relationship*
Cause-related	Re-adjusted***	Social***
Sales promotion	Re-adjusted***	Promotional***
	Newly Created****	Placement****

*category scope kept as suggested by Tafesse & Wien (2017), **category definition has been changed to meet sample characteristics' in the line with original definition and a new name has been proposed, ***category has been split in to two or more categories based on sample characteristics', ****categories added based on extracted sample.

3.5 Rating of Non-Count Variable

The non-count variables are rated based on variable complexity or dimension. The rating is based on earlier researches as shown in Table II.

Table 2. Rating for Content Structural Elements

S. No	Element	Variable Type	Categories	Rating	Based on
1	Theme	Non-count	*Refer table 2*	N/A	Tafesse & Wien (2017) and author's judgment
2	Type*	Count	*Text*	1	Tefesse, 2015; Moran, 2019
			Link	2	
			Photo	3	
			Album	4	
			Video	5	
3	Perceived Action*	Count	*Click*	1	de Vries et al. 2012; Tefesse, 2015; Moran, 2019; Author Judgment
			Interaction	2	
			Subscription	3	
			Conversion	4	

Table 2 continued on next page

Table 2 continued

S. No	Element	Variable Type	Categories	Rating	Based on
4	User Involvement*	Count	*View*	1	Calder and Malthouse, 2008; Author judgment
			Listen	2	
			Read	3	
			Participate	4	
5	Target Audience*	Count	*Internal*	1	Alboqami et al.,2015; Newberry, 2019; Author Judgment
			External	2	
			Not Specified	3	

*non-count variable converted to count

4 ANALYSIS AND FINDINGS

4.1 Interpreting Theme Mix (Base-Model)

Any variable with a communality value lesser than 0.5 may struggle to load significantly (Hair et al., 2010). Hence, the commonality measure of the data for each post were evaluated and posts with communality measures below 0.5 were excluded in the factor analysis. In total, 126 and 86 posts from the global (0.421 to 0.845) and Indian (0.321 to 0.963) samples were omitted respectively.

The factor analysis was used to determine the base model for both the sample groups. For global, 1757 posts explaining 81.126% of variance loaded onto six factors attributable to 13 themes and 1364 posts for Indian loaded onto five factors explaining 70.826% of variance attributable to 11 themes. Table III illustrates four distinct theme models for both global and Indian samples. The BM (-1) was found to be the most efficient model for both the global and Indian samples. The pattern obtained from the analysis suggests that the base model can be improved by removing low contribution themes initially. However, it tends to fall when more than one theme was removed with BM (-2). The overall analysis indicates that BM is the second best fit model for any combination which can be obtain through PCA analysis of PI values.

Table 3. Theme Mix Model

Global					Indian			
	Base-model (BM)	BM(+n)	BM (-1)	BM(-2)	Base-model (BM)	BM(+n)	BM (-1)	BM(-2)
	Base-model (Themes obtained from PCA)	BM plus rest of the themes	BM less Brand Community	BM (-1) less Employee, Placement and Relationship	Base-model (Themes obtained from PCA)	BM plus rest of the themes	BM less Current Event and Emotional	BM(-1) less Relationship
Constant	1.245	2.145	2.169	2.144	0.721	1.972	2.156	1,846
p-value	0	0	0	0	0	0	0	0
R^2	0.55	0.77	0.81	0.74	0.47	0.75	0.77	0.72
Adjusted R^2	0.71	0.49	0.76	0.69	0.69	0.41	0.73	0.67

Note; Base-model represents the mix of themes obtain through factor analysis. Mix (+n) represents themes added to the base-model and Mix (-1,-2) represents base-model less theme category.

Table 4. Content Elements Parameter Estimates

			Global				Indian		
Parameters	**Rating**	**Like**	**Share**	**Comment**	**Reaction**	**Like**	**Share**	**Comment**	**Reaction**
Text	[Ty=1]	**BL***	**BL***	**BL***	**BL***	**BL***	**BL***	**BL***	**BL***
Link	[Ty=2]	0.958*	0.762*	0.651*	-	-	0.066*	0.024*	0.167*
Image	[Ty=3]	0.9*	0.776*	0.417*	0.897*	0.049*	0.696*	0.345*	0.75*
Album	[Ty=4]	0.833*	0.687*	0.437*	1.051*	1.303*	0.206*	1.005*	0.505*
Video	[Ty=5]	1.33*	1.066*.	1.718**	0.652*	1.275*	0.284*	0.067**	0.492*
Click	[PA=1]	**BL***	**BL***	**BL***	**BL***	**BL***	**BL***	**BL****	**BL***
Interaction	[PA=2]	0.589*	1.13*	0.73*	1.064*	0.013*	0.003*	0.091*	0.077*
Subscription	[PA=3]	0.639*	-	0.395*	1.145*	0.007*	0.002*	0.103*	0.062*
Conversion	[PA=4]	0.598*	-	0.341*	0.856*	0.004*	0.002*	0.069*	0.045**
View	[UI=1]	**BL***	**BL***	**BL****	**BL****	**BL***	**BL***	**BL***	**BL****
Listen	[UI=2]	1.143*	1.204*	1.847*	-	1.006*	-	1.975*	0.215*
Read	[UI=3]	2.406*	1.157*	2.224*	1.554*	0.083*	-	2.048*	0.222*
Participate	[UI=4]	-	1.927*	0.986*	-	0.065*	1.098*	2.015*	0.166**
Internal	[TA=1]	**BL***	**BL***	**BL***	**BL***	**BL***	**BL***	**BL***	**BL***
External	[TA=2]	1.296*	1.012*	0.772*	1.264*	0.065*	-	0.91*	0.043*
Not Specified	[TA=3]	1.335*	1.368*	1.509*	1.294*	1.237*	0.723*	0.567*	0.076*

Note: BL represents the baseline variable for each element where *Significance at 0.05 and **significance at 0.01; (p < 0.05, 0.01 = null hypothesis rejected)'-' represents the elements identified to be not statistically significant with the hypothesis testing

4.2 Theme Structural Efficiency

Tables IV represents the statistical significance of the elements tested at a 95% level of confidence, and the parameter estimates based on exponential beta *(exp β)*. Testing hypothesis for 'Like' suggest that H_0 got rejected for each of the elements at all levels except UI-4 *($H_0$5a4, p=.218, p>0.05)* for global samples and Ty-2 *($H_0$2a2, p=.878, p>0.05)* for Indian samples. For 'Share', H_0 got rejected for all elements except PA-3 *($H_0$3b3, p=.194, p>0.05),* PA-4, *($H_0$3b4, p=.555, p>0.05),* TA-2 *($H_0$2b2, p=.625, p>0.05)* for global sample. Indian sample resulted in rejection of H_0 for all elements at all level for 'Share' except UI-2 *($H_0$4b2, p=.206, p>0.05),* UI-3 *($H_0$4b3,p=.094, p>0.05*) and TA-2 *($H_0$5b2, p=.704, p>0.05*). The entire set of H_0 for 'Comment' got rejected for both global and Indian samples. Ty-5 and UI-1 for a global sample and Ty-5 and PA-1 for the Indian sample were rejected at 99% level of confidence. The entire set of H_0 for 'Reaction' got rejected for the Indian sample, where UI-1 and UI-2 were rejected at 99% level of confidence. For global sample, all H_0 has been rejected except three; Ty-2 *($H_0$2d2, p=.176, p>0.05),* UI-2 *($H_0$4d2, p=.589, p>0.05)* and UI-4 *($H_0$4d4, p=.181, p>0.05).* Thus in total, seven null hypothesis for global and four for the Indian samples were accepted. According to the findings, the Read element (UI-3) can increase Like by 2.406 times (24.6 percent approx) and Comment by 2.048 times (24.8 percent) for global and Indian samples, respectively. For both global and Indian samples, these are the highest of all parameters. Baseline estimations were considered to be one, hence no effect on engagement was observed for any given parameter. The increase (>1) in engagement for the global sample with Type has been estimated for Album (R=1.051), Video (L=1.33, S=1.066, C=1.718) and decrease (<1) has been estimated for Image and Link. Only Reaction showed an estimated increase in engagement for PA-2 and PA-3. For every given level of PA, the rest of the interactions were expected to decrease for the entire sample. Except for UI-4 for Comment, UI estimates showed an increase for all interactions at all levels (0.987). Except for the Comment at TA-2, all interactions were projected to increase for TA at all levels (0.772). The biggest TA increase was predicted for Comment at TA-3 (1.509). The highest global sample drop was predicted for Comment at UI-4 (0.986), implying that 98.6 percent of comments are likely to decline with post-expecting user participation. For the Indian sample, engagement is expected to rise for Like at Ty-4 (1.303) and Ty-5 (1.303). Ty-4 (1.005) was estimated to have a higher comment increase, whereas the rest of the Ty levels were estimated to have a lower interaction. For the Indian sample, PA at all levels tends to decrease for all types of interaction, with Comments at PA-3 (0.103) being the most affected. For example, UI-2 (1.006) is expected to rise, whilst UI-3 and UI-4 were expected to fall. Share is likely to increase for UI-4 (1.098) rests were found to be not significant. Comment has been estimated to increase at all levels of UI with the highest being estimated for UI-3 (2.048). The reaction has been estimated to decline for all UI levels. All levels of TA tends to decline for all types of interaction for Indian samples except for Like at TA-3 (1.273). The highest decline has been estimated for Comment at TA-2 (0.91).

5 DISCUSSION

The descriptive analysis indicates that a bigger community size corresponds to a higher level of engagement volume ($Global_{eng}$>$Indian_{eng}$ and $Global_{cs}$>$Indian_{cs}$). However, it leads to a falling PI ratio: {$Indian_{PI}$ (16.6%)>$Global_{PI}$ (6.8%)}. Differences in contribution score and PI rates of themes imply that different themes produce varying levels of engagement (Alboqami et al., 2015; Gruen et al., 2006). The regression analysis suggests that overall engagement efficiency can be increased by avoiding low contribution themes. The element analysis in content structure is consistent with previous research findings that demonstrate an *exp β* reduction with increasing UI and PA (Moran et al., 2019; Tefesse, 2015; Subtle, 2014). On the other hand, with a high level of vividness, engagement is likely to rise (Tefesse, 2015). According to *exp β* estimates, the most appropriate structure for a global sample is *'a Video appealing for subscription with reading involvement targeted towards a non-specified audience is most likely to increase engagement through share and like'.* The same interpretation for the Indian sample suggests that *'an album with subscription appeal and reading involvement targeted at a broader audience is most likely to increase engagement through like and comment'.* This interpretation can be applied to any form of interaction depending on the type of content. For example, the most 'Like' generating global theme was 'Learning,' with 0.251 contributions (25.1 percent), followed by 'Emotional,' with 0.212 for share. Now if a page wants to target 'Like' then the findings of the study suggest that it publishes *'a learning video with click interaction with reading involvement targeted towards not-specified audience'.* The technical standing for content structure is Interaction $_{Like}$ = Structure {TY=5, PA=1, UI=3, TA=3, CT=Learning}. For the Indian sample, the 'Students' post obtained 0.719 contributions for like and 0.406 for comment. The study suggests publishing *'a student-related album with conversion participation with reading involvement targeted towards not-specified audience'*. Reading involvement for 'Like' *($TA=3_{Like}=0.083$)* has been estimated to decrease however comment is estimated to increase by 2.048 which is highest among all the exp β obtained. The technical standing is *Interaction $_{Like+comment}$ = Structure {TY=4, PA=4, UI=3, TA=3, CT=Student}*. Similarly, the study identifies the most avoidable content structures, such as *'a promotional post containing a link ($TY=2_{Like}$, 0.958) for conversion ($PA=4_{Reaction}$, 0.856) through participation ($UI=4_{Comment}$, 0.986) targeted towards the external audience ($TA=2_{Comment}$, 0.772)'*. The above statement contained structural elements with *exp β* less than one, and the theme 'Promotional' was included because it has the lowest contribution per interaction (Table V). It illustrates the contribution scores per interaction for each theme which represents the most interacted interaction. Informative contributes highest towards Comment (at 0.49) and Experiential (at 0.21) contributes highest towards Share. For Indian samples, Students dominate all contributions per interaction across all themes with a 0.71 contribution value. The analysis suggests that when a page intends to target Like from the global sample, it should use Learning and the Indian should use Students as per adjusted optimized content structure obtained from the parameter analysis.

Table 5. Theme Contribution Scores

GLOBAL					INDIAN				
Theme	**Like**	**Share**	**Comment**	**Reaction**	**Theme**	**Like**	**Share**	**Comment**	**Reaction**
Learning	**0.251629**	0.097477	0.335363	**0.391481**	Student	**0.7196**	0.299135	**0.406946**	0.082131
Informative	0.11002	0.026966	**0.495891**	0.075931	Placement	0.004186	**0.354985**	0.212917	0.366265
Experiential	0.11031	0.00401	0.048838	0.064755	Learning	0.002898	0.27934	0.182229	**0.397687**
Emotional	0.079468	**0.212376**	0.022113	0.095256	Experiential	0.060599	0.012615	0.104452	0.025297
Current Event	0.083969	0.189363	0.015873	0.09554	Institutional	0.021301	0.028644	0.045965	0.102553
Students	0.089026	0.050451	0.021346	0.105032	Brand Community	0.009287	0.015276	0.012254	0.011603
Social	0.073963	0.146455	0.016633	0.07773	Event	0.007516	0.004258	0.006394	0.003475
Institutional	0.053159	0.131444	0.012986	0.054084	Emotional	0.002511	0.001365	0.008802	0.003235
Relationship	0.062486	0.010425	0.013864	0.008995	Relationship	0.008815	0.001342	***0.00313***	0.003102
Brand Community	0.033825	0.03537	0.004656	0.010974	Brand Resonance	***0.002298***	***0.001172***	0.008535	0.002056
Brand	0.02804	0.01649	0.007319	0.017901	Employee	0.147182	0.000685	0.003344	0.001338
Employee	0.008718	0.000945	0.000735	0.001254	Informative	0.168152	0.000895	0.003077	***0.000532***
Placement	0.003011	***0.000566***	***0.000444***	***0.000476***	Promotional	0.044475	0.000289	0.001953	0.000727
Promotional	***0.000865***	0.000725	0.003938	0.000592	Social	0.018585	0.015276	0.012254	0.011603

6 IMPLICATION

The study provides a critical understanding of content structure that can be used to project and estimate engagement. Earlier research provided sufficient structural knowledge (excluding theme) for producing engagement but did not provide a clear methodology for determining the adjustable content theme for a particular structure based on interaction. It extends the usage of previous models to the higher educational institution's Facebook contents and quantifies a theme that was previously provided as a qualitative metric. Assuming that each page has access to its own historical data, the study recommends determining the best content structure.

Implementation Methodology

a. Target Interaction

The implementation must be based on the "target interaction" concept (Moran et al., 2019). Target interaction refers to the interaction option that a page intends to target with a piece of content. Each page must determine the most likely target interaction based on contribution value and parameter estimates of content structure. Figures 3 and 4 illustrate the shift in estimates when targeting 'like' and 'share,' respectively. The curves in the figure that are less than one represent those that are likely to decline while targeting a specific interaction.

b. Impact of Target Interaction

Once a page has decided on the target interaction, it must calculate the impact of targeting. The impact of the target has been defined as the interaction opportunity cost of targeting a specific interaction. The equation below shows how to calculate the target interaction value and impact value.

$$\text{Target Interaction Value}_{(L/S/C/R)} = \sum \left(optimized\ \ strcutal\ \ units\ \ x\ \ target\ \ theme\ \ contribution \right)$$

$$\text{Impact Value} = \sum \left(non\ \ optimized\ \ structural\ \ units\ \ x\ \ \ target\ \ theme\ \ contribution \right)$$

*Note: Estimate ³ 1 should be considered as positive and £ 1 as negative
*Here, Impact value is the opportunity cost of engagement against a target interaction.

Table 6. Target and Impact Estimates

Elements	Target	Impact	Impact	Impact
	Like	Share	Comment	Reaction
Album	1.303	0.206	0.005	0.505
Click	1	1	1	1
Listen	1.006	0	1.975	0.215
Not Specified	1.237	0.723	0.567	0.076
	Share	Like	Comment	Reaction
Text	1	1	1	1
Click	1	1	1	1

Table 6 continued on next page

Table 6 continued

Elements	Target	Impact	Impact	Impact
	Like	**Share**	**Comment**	**Reaction**
Participation	1.098	0.065	2.015	0.166
Internal	1	1	1	1
	Comment	Like	Share	Reaction
Album	1.005	1.303	0.206	0.505
Click	1	1	1	1
Read	2.048	0.083	0	0.222
Internal	1	1	1	1
	Reaction	Like	Share	Comment
Text	1	1	1	1
Click	1	1	1	1
View	1	1	1	1
Internal	1	1	1	1
	4	4	4	4

Figure 4. Target 'Like' for Indian Sample

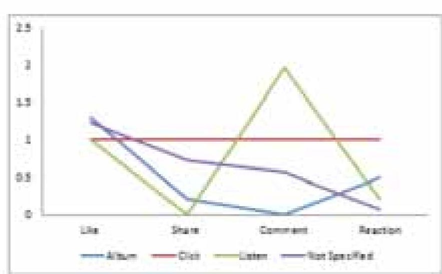


Figure 4: Target 'Like' for Indian sample

Figure 4 illustrates estimated impact on interaction for 'Target Like'. The fall for Share (Alb=0.206, Ns=0.723), Comment (Ns=0.567) and Reaction (Alb=0.505, Lis=0.215 and Ns=0.076) are shown in table VI.

Figure 5. Target Share for Indian Sample

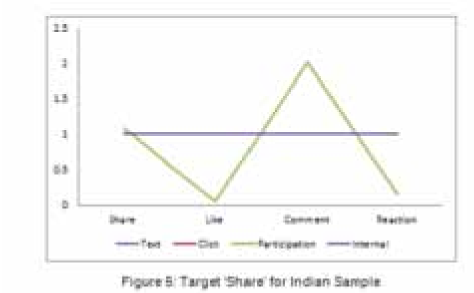


Figure 5 illustrates the movement of estimates for ‘Target Share’. The optimized structure (Table VIII) suggests majority of the contents at baseline are likely to increase Share interaction; however like and reaction are supposed to fall with UI-4.

Figure 6. Aggregate Estimates

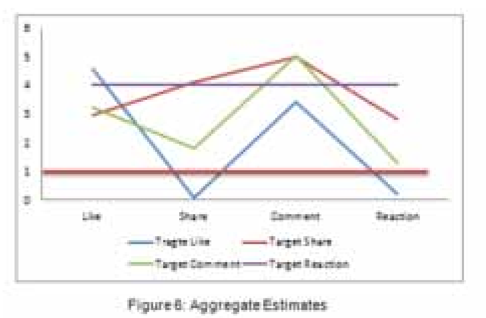


Figure 6 illustrates the aggregate estimates for each interaction, as well as their respective movement for impact interactions. It demonstrates that targeting share rather than like results in higher engagement performance, despite the fact that like is the most common interaction choice for any given content theme. The only target interaction estimate to fall below baseline has been observed with Like.

Table 7. Target Estimates

	Like	Share	Comment	Reaction
Target Like	4.5656	0.071	3.413	0.204
Target Share	2.935	4.098	5.015	2.834
Target Comment	3.22	1.794	5.053	1.273
Target Reaction	4	4	4	4

c. Estimating Impact Gap

The Impact Gap (Figure 5) is the estimated change in volume of interaction based on target interaction calculated as follows:

Impact Gap = $\text{Target}_{\text{interaction}}$ Elements – $\text{Impact}_{\text{interaction}}$ Elements.

Figure 7 illustrates the Impact Gap for the above-mentioned target like and target shares. The curves' movement suggests that 'target like' estimations have a larger interaction opportunity cost than 'target share' estimates. Impact values (Table VIII) can be determined for each interaction based on the desired combination.

Figure 7. Impact Gap Curve

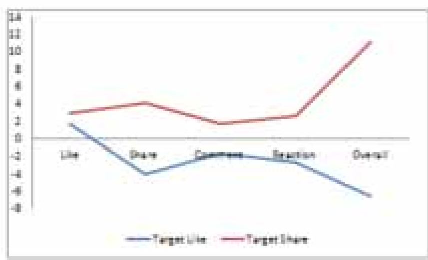


Figure 7: Impact Gap Curve

Table 8. Impact Values for Target Interaction

		Aggregate		
Target	Impact			Total
Like	Share	Comment	Reaction	
4.5656	0.071	3.413	0.204	7.684
Share	Like	Comment	Reaction	Total
4.098	2.935	5.015	2.834	14.882
Comment	Like	Share	Reaction	Total
5.053	3.22	1.794	1.273	11.34
Reaction	Like	Share	Comment	Total
4	4	4	4	16

Therefore the interaction optimization for Indian sample can be achieved with 'target share' content structure. Based on contribution score, *Placement* (0.354985) is most likely to increase share at highest rate. Hence the technical structure for content optimization at lowest impact is: $\text{Interaction}_{\text{share}}$ = (*Placement, Ty=1, PA=1, UI=1, TA=1).*

LIMITATIONS

The study only deployed a meta-description of a post to determine content category due to the lack of a comprehensive categorization framework. Hence, future studies can develop a better model by initially developing a precise categorization framework applicable to higher educational institutions.

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