Comparative analysis of performance of educational content during pre-lockdown and lockdown periods in India

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Abstract

This paper presents a comparative analysis of educational pages' 'post interactions' in two time periods. It evaluates the user behaviour pattern – specifically, the impact of lockdown on interactions by collecting online social data through real time data extraction tools and statistical tests like correlation, equation modelling and regression analysis. The study investigates frequency of user interactions and growth of specific content type along with impact of lockdown on educational posts. The study also provides insights on the impact of page activeness on content performance and user intention of interaction through volume growth and content performance analysis, and suggests user intention and structure of optimized content mix for better performance.

Keywords: Social Media Communication, Communication Development, Engagement Rate, Share of Voice, Facebook Marketing

Introduction

Web 2.0 is the IT infrastructure where multiple media platforms facilitate exchange of user generated content (Kaplan and Haenlein, 2010). The era of web 2.0 has been a constant disruption to existing technologies and web phenomenon. One such disruption is social media which has been defined as "websites and applications used for social networking" by the Oxford dictionary (2011). The rise of interactive platforms and penetration of Internet have enhanced the power of communication effectiveness in the form of real time engagement. Along with opening new ways of communication, social media has also developed a new paradigm of analytics. Social media communication can be labelled under different heads as per theme and message intent. This is one of the fastest and widest network of communication when it comes to larger geographic coverage. The Covid-19 pandemic has forced academic institutions and all other types of educational institutions to cease operations, resulting in a complete crisis within the sector. In India, many digital platforms for education have seen a surge in user growth. Government of India has launched many initiatives like DIKSHA, SWAYAM, etc. Educational institutions in India had started adopting the social web ecosystem by the beginning of 2010. Almost every educational institution has its own social network comprising multiple platforms covering a large audience. In recent years, while total digital ad spend has registered high growth in India, ad spend by the education sector is in decline since 2015 (IAMAI report on digital ad spending in India). This is an indicator of dissatisfaction with the results obtained from the marketers' perspective. So far, the use of social media for communication development by higher educational institutions can be broken down as - enhancing relationships, improving learning motivation, offering personalized courses and developing collaborative abilities (Wheeler, Yeomans and Wheeler, 2008). During the pandemic, digital mode of learning gained a lot of popularity and size of community increased for several educational social media accounts. Thus, it is very important to evaluate the intent of user engagement and role of social media in communication development in education during the pandemic period.

Literature Review

Social media can be categorized as collaborative projects, blogs and micro blogs, content communities, social networking sites, virtual game worlds, and virtual communities (Zhang et al., 2015). Primary goals of social media activities are - community expansion, relationship development, and enhancing awareness and communication (Michaelidou et al., 2011). The other priority goals of social media activities generally focus on awareness, conversion, communication, relationship development, and retention activities (Thomas, 2011; Stokes, 2013). Communication development over social media networks takes place through some technical elements. The engagement elements in social terms of communication can be called “pass-on” and “endorsement”. The “pass-on” interactions are driven by cognitive-inducing actions and “endorsements” are driven by the customer's level of perceived exposure to marketing action of the brands (Ananda et al., 2019). Social media marketing takes place through some activity elements like “Entertainment”, “Interaction”, “Trendiness”, “Customization” and “Word-of-Mouth” (Kim and Ko, 2011). Social media programs are dependent on user activities, and user activeness is highly impacted by both internal and external factors. The degree of user activeness is highly dependent on content flow path. Audience plays a key role in communication development as the audience is empowered by technology to develop its own communication and generate social spread. The impact of audience participation in organic social reach and spread has a greater impact on satisfaction than promotional activities through pull or push tactics, as suggested by Ramanathan et al. (2017). The values and interest shared by the audience influence the rate of interaction as content strategy is highly influenced by audience homogeneity through identity and sentiment (Weng et al., 2011). Socialization plays a key role in motivating users to use social media. Technical utilities analysed in the study strongly suggest that sharing of content further initiates digital interaction (Shukla et. al., 2020). The purchase behaviour over online shopping is highly impacted by Electronic word-of-mouth (e-WOM). Satisfaction and e-WOM both contribute towards user purchase decisions (Srivastava and Singh, 2020). Community commitment and trust is the key to audience participation resulting in high degree of social media engagement (Vorah and Bhardwaj, 2019). The role of community in communication development significantly impacts overall performance as it helps in increasing reach, engagement and community size at a faster rate (Rossmann et al., 2015). The credulity, empathy and relevance of audience generated and spread content is observed to be greater than page generated content (Gruen et al., 2006). A majority of young Internet users make use of one or more forms of online social media (Barenblatt, 2015). Teenagers and adolescents are fast adopters of online platforms (McCrindle and Wolfinger, 2010; MacKenzie et al., 2012; James and Levin, 2015). User attitude should be of prime concern for organizations involved in social media activities (Cox, 2010). Cognitive and behavioural responses get boosted with online WOM activities, which further has a ripple effect on social media (Kumar et al., 2013). Other studies (Yang, 2012; Gensler et al., 2013; Hamidizadeh et al., 2012; Kumar et al., 2013; Tan et al., 2013; Labrecque, 2014; Boateng and Okoe, 2015; Liu et al., 2015) have conducted research focused on the role of attitude on decision making primarily for teenagers and young adults. Human nature supports social media activities as communication is the key for activities like reaction, comment or share (Uitz, 2012). Users of social media can be classified as: creators, critics, collectors, joiners, spectators and inactives based on participation (Li and Bernoff, 2008). Types of engagement in social media include comment and share (Dhaoui, 2014). Liking is an endorsement; comment can be a reply, feedback or conversation, and sharing is a recommendation (Dhaoui, 2014). Sharing, communicating and relating are key elements in social media (Hennig-Thurau et al., 2010). Exposure of the audience to a post or ad is termed as 'reach' (Aksakalli, 2012). “If a certain user clicks on a “Like” button on a post, other users that visit the post might see that the user liked it, and a story might even appear on the user's timeline showing that he or she liked the post” (Facebook, 2016). Liking is as crucial as other elements as it extends the reach by getting shared within the individual's network (Swani et al., 2013). Liking is endorsing without comment (Hennig-Thurau et al., 2004). “Favorite” is endorsement and “retweet” is recommendation on Twitter (Alboqami et al, 2015). Liking, sharing and commenting, all contribute to extending reach (Liu et al., 2017: Alboqami et al., 2015; Hennig-Thurau et al., 2004). Pass-on engagement is recommendation behaviour such as: sharing a post on Facebook or a video on YouTube; retweeting a tweet on Twitter; re-blogging on a blog; or reposting on Instagram or a blog. Endorsement engagement denotes affective responses covering behaviours such as: liking a post on Facebook, a “gram” on Instagram or a video on YouTube; adding a tweet as 'favorite' on Twitter; or pinning a “pin” on Pinterest (Liu et al., 2017). Any content movement in communication development over social media is impacted by audience “opinion passing” and “opinion seeking” behaviour, and those highly effected by trust and quality of the content, whereas audience homogeneity is not a significant factor for multi-directional eWOM (Chu and Kim, 2015). The endorsement rate is highly dependent on brand credentials, and engagement pattern varies according to segment and characteristics of the segment (Dhaou, 2014). Whiting, Williams and Hair (2017) analysed “Post” “Like”, “Share”, “Comment”, “Community Communication” for engagement to identify drivers of positive and negative eWOM. 'Following' can be more effective when the marketer wants to increase the size of the community, but when the objective is to communicate with the existing community, 'like' and 'comment' are more measurable parameters. User behaviour can be impacted on the basis of platform interface and user intent (Virtanen et al., 2017). Social media engagement is a comparatively simpler and more cost-effective form of consumers' online brand-related activities framework, which was first proposed by Muntinga et al. (2011) and later extended by Tsai and Men (2013). The framework suggested that consumers generally play three types of roles in social media content engagement - “consumption”, “contribution” and “creation”. The lowest level of engagement is consumption; under this type of engagement, the consumer passively consumes content without direct participation. Contribution is the second level of engagement; under this type, the consumer participates through peer-to-peer and peer-to-content interactions. The highest and strongest level of engagement is creation; under this type of engagement, the user generates content and interaction of such content takes place between users. Perceived social media activeness enhances effectiveness of customer relationship and loyalty (Ismail, 2017). Viral posts are capable of generating opinion seeking, opinion giving and opinion passing actions, which are the major drivers behind generating eWom (Chu and Kim, 2011). Content should have appeal to encourage opinions, which, in turn, enhances multi-directional communication (Chu and Kim, 2011). Brennan and Croft (2012) carried out social media content analysis based on platform and applicability, and reported that not all types of content can generate similar volume of engagement for different samples within the same platform and application area. Interactive content with informative element has the highest potential for engagement; specifically, hyperlinks for communications initiate forward movement. *Hashtags* and mentions are the key drivers for electronic word-of-mouth (Alboqami et al., 2015). “Entertaining”, “emotional” and “interesting” content highly influence social media engagement (Barger et al., 2016). Evaluating the social media marketing conceptual framework, as suggested by Keegan and Rowley (2017), includes 6 elements: setting evaluation objectives, identifying key performance indicators (KPIs), identifying metrics, data collection and analysis, report generation and management decision making. Time scheduling in social media activity leads to an increase in user participation based on high and low performing time range (Aksakalli, 2011). An indirect organic interaction has higher potential of conversion than a referral interaction over Facebook (Rebecca, 2019). The session duration is highly impacted by the extent of 'marginal return effectiveness'. The hierarchy suggested by the study for most effective visits are direct visitors followed by search engine generated visitors and lastly, the attached link generated visitors (Plaza, 2009).

Objective of the Study: To understand the pattern of educational social media page performance and content engagement.

Framework Studied

A framework for categorizing social media posts by Wondwesen Tafesse & Anders Wien (2017) is taken as the basis with categories - emotional, functional, educational, brand resonance, experimental, current work, personal, employee, community, customer relationship, cause-related and sales promotion.

Table 1: Classification of content suggested by Wondwesen Tafesse & Anders Wien

Proposed Categories	Definition and Content Message Theme
Emotional	These brand posts evoke consumers' emotions. To this end, posts typically employ emotional language, inspiring stories or humour and jokes to arouse affective responses, such as fun, excitement and wonder. Common themes: emotionally worded posts, storytelling, jokes and humour.
Functional	These brand posts highlight functional attributes of the company's products and services. Typically, these posts promote the benefits of the company's products and services according to performance, quality, affordability, design and style criteria. Common themes: product functional claim, product reviews, awards, green credentials, and so forth.
Educational	These brand posts educate and inform consumers. These posts help consumers acquire new skills on proper ways of applying products, or discover new information about broader industry trends and developments. Common themes: do-it-yourself tips, instructions, blog posts, external articles, technical interviews with employees, etc.
Brand resonance	These brand posts direct attention to the brand promise and identity of the focal brand. These posts highlight brand identity such as brand image, brand personality, brand association and brand products with the goal of differentiating the brand and favourably influencing consumers' brand attitude and association. Common themes: brand image, product photo, etc.
Experimental	These posts evoke consumers' sensory and behavioural responses. Common themes: sensory simulation, physical simulation, brand event, etc.
Current event	These brand posts comment on themes that capture an active talking point with the target audience, such as cultural event, holiday, etc. Common themes: weather, cultural event, TV show, etc.
Personal	These brand posts are centred around consumers' personal relationships, preferences and experiences. Common themes: friends, family, personal preferences, etc.

Proposed Categories	Definition and Content Message Theme
Employee	These brand posts are about employees. These posts reflect employees' perspective on a range of issues such as employees' technical expertise, their managerial philosophies or personal interests, hobbies, etc.
Community	These brand posts promote and reinforce the brand's online community. These brand posts foster a sense of community identification and engagement. Common themes: encouraging fans to become members of the brand's online community, acknowledging fans, etc.
Customer relation	These brand posts solicit information and feedback about consumers' need expectations and experiences. Common themes: customer feedback, customer testimony and customer reviews.
Cause related	These brand posts highlight socially responsive programs supported by focal brand.
Sales promotion	These brand posts entice customers to take action towards a buying decision. Common themes: price discounts, coupons, free samples, customer contests and competitions.

Framework for content classification

The current framework has been developed by analysing the content during the period January-July 2019 by primarily using the framework of Wondwesen Tafesse & Anders Wien (2017). After analysing the content, 5 new types have been introduced, 6 types from the initial framework have been retained and 6 were dropped. Additions to the framework for content analysis were - Learning, Recognition, Awareness, Event and Informative. Educational, Promotion, Alert (Update), Brand Community, and Cause (Social) were retained. Brand Resonance, Experimental, Employee, Functional, Personal and Customer Relation were dropped.

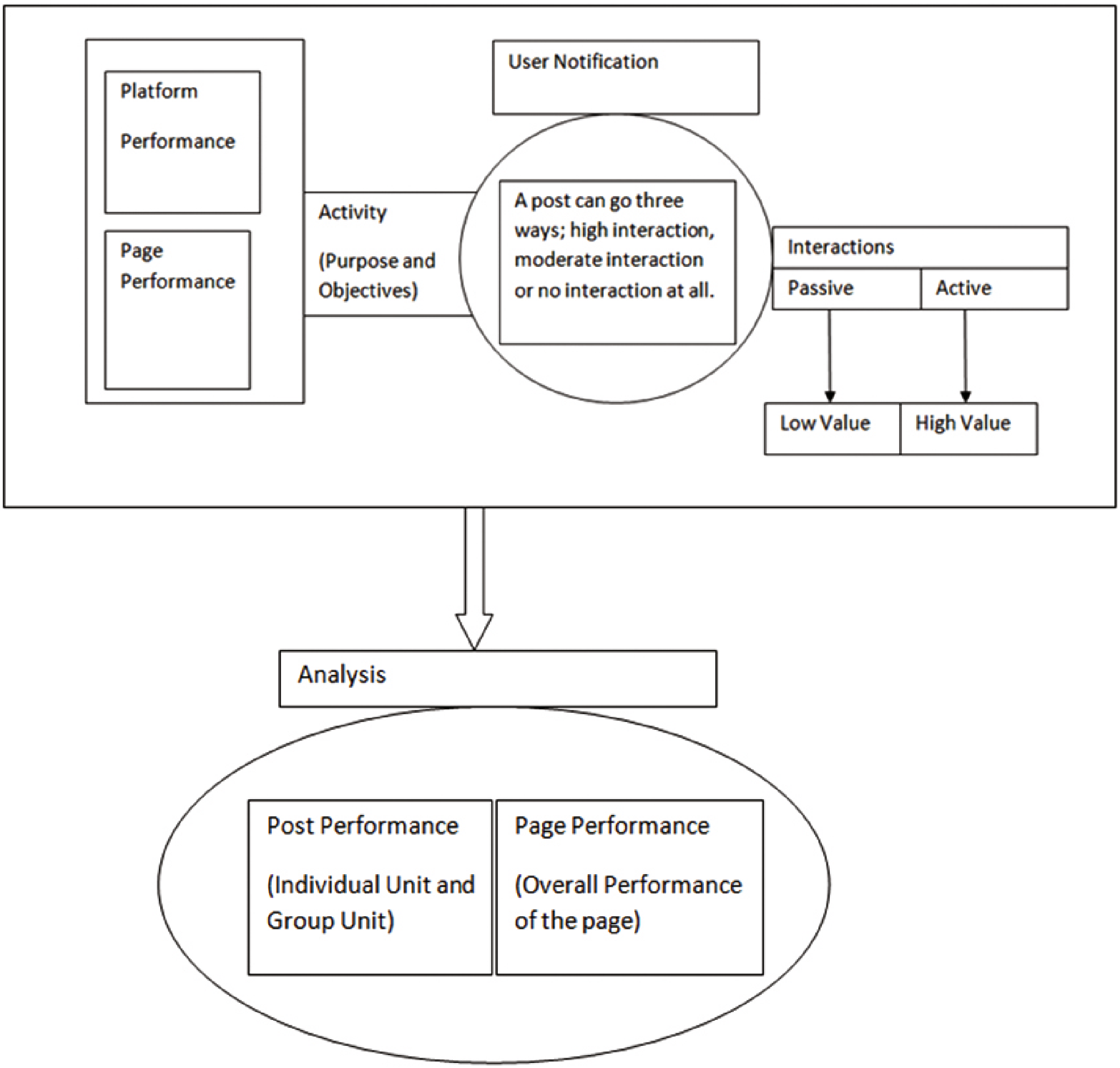
Table 2: Content Groups for the study

Content Group	Definition
Awareness	Any post that aims to enhance user knowledge about any topic, product or service, but doesn't ask for direct conversion and also cannot be paid content.
Event	Any post with information about an upcoming occasion to be held live online or offline, or both. It is a kind of an update post but directly linked with an occasion.
Educational	Any post that aims to enhance user knowledge directly or indirectly (related to academics); mostly comes with follow up steps.
Informative	Any post that aims to enhance users' existing knowledge by providing information on any subject.
Learning	Any post that asks for user interaction to enrich existing knowledge or skill; may or may not be directly linked with academics.
Promotional	Any post that motives the user for conversion, but with self declaration as an ad or paid content.
Recognition	Any post that provides recognition to any individual or group, or anything else.
Social	Any post that represents social context in the body and aims to spread awareness about the subject.
Update	Any post that comes as a follow-up to an existing post.

Framework for Measurement

The literature review extensively indicated the role of on-page engagement elements in social media interaction process. The elements of interaction can be grouped under 'post level' (segregated engagement) and 'page level' (aggregated engagement). The overall page performance is the result of engagement volume generated by individual posts in a given time. Content performance is the result of engagement generated by a content group for the same period of time. Hence, the following process has been used in the study to collect and analyse the data.

Figure 1: Measurement framework



Scope of the Study

The study focuses on content classification for post engagement rate by determining reception of content and overall page performance. Findings are applicable only to pages with similar target and content. The study has not considered the technical aspects of content and platforms to generalize it beyond the specific target audience of the samples. However, comparative approach of the study on the dimension of content and engagement for performance analysis is applicable for all types of pages and audience.

Significance of the Study

The findings of the study enhance the capability of publishers to categorize the types of content specifically in the field of education and provide insights for user assessments for need identification and development of content mix to enhance post engagement and page performance.

Methodology

The overall analysis has been conducted under two timelines Phase 1 (1st January 2020 – 22nd March 2020) and Phase 2 (23rd March 2020 to 17th May 2020).

Growth Analysis (Descriptive)

The samples were analysed with 4 parameters - Community (C), Engagement (E=like, comment, share and reaction), Reach (R) and Post Interaction (PI). The growth of the elements between phase 1 and phase 2 has been calculated and comparative analysis of the samples was performed. The analysis has been conducted by calculating growth rate of each element per sample. Formula used for the growth rate is:

$GR = \frac{E1P2 - E1P1}{E1P1} X\ 100$, where E (1,2,3.....,n) value of the element and P (1,2) represents the phase, i.e E1P1 is the value of the element in phase 1.

Performance Analysis

Performance of the samples was analysed based on an aggregate score termed as 'performance rating'. The rating is a value between 0 to 1 calculated in two steps according to the performance ranking formula.

Step 1: $p = \{(Cx1.5) + (Ex1.7) + (Ax1.6) + (Gx1.7) + (ERx1.5) + (Sx1.3)\}$ where 'C' is Community Size, 'E' is Engagement, 'A' is Activeness, 'G' is Growth, 'Er' is Estimated Reach and 'S' is Share of Voice.

The weighted scores for each element were determined through correlation analysis of each sample. The element with the highest correlation with overall 'page interaction' has been weighted highest among the elements, and the element with lowest correlation has been weighted lowest. Here, Engagement comprised 'Like' (L), 'Comment' (C), 'Share' (S) and 'Reaction' (R). The overall 'E' value has been determined by an Engagement equation i.e.

$$E = \{(Sx1.3) + (Cx1.2) + (Lx1.1) + (R)\}$$

The weighted scores for engagement were determined according to the relevance in communication spread of Facebook algorithm.

Step 2 : $Performance\ Rating = \frac{Psn}{Largest\ PS}$, where '$P_{Sn}$' is Performance Score of the sample.

The 'p' values obtained in Step 1 were converted between 0 to 1 with the above formula for representation and final indexing.

Content Reception Analysis

The total number of posts by the sample units during the time length of the study were analysed on 4 parameters - Frequency (F), Community (C), Estimated Reach (Er) and Engagement (E). Further, the content was categorized according to the 'appeal' as per the content segregation framework and indexed on the basis of the 'Content Performance Score' (CPS).

$$\boldsymbol{CPS = \frac{E}{F + C + Er}}$$

The most performing content types according to CPS were considered as base level content mix for regression analysis taking 'Content Performance Score' (x) as the independent variable and Page Performance Rating as the dependent variable (y).

Sampling

An initial survey with 562 respondents was carried out through Google Forms for sample selection. The respondents belong to higher educational segment comprising both students and faculties. In the survey, respondents were asked to name any 10 government and non-government websites, applications, social media pages related to education, which they have visited in the last 3 months or intend to visit shortly. In total, 486 valid responses were received.

Sample Elimination

Criteria 1: Samples with less than 30% frequency were eliminated.
Criteria 2: Samples which belong to any state-level institution or individual were eliminated.
Criteria 3: Samples with no activity during either of the two phases were eliminated.

Platform Selection

Initially, the social media platforms, namely, Facebook, Twitter, YouTube and Instagram profiles of the selected samples were visited and community size was recorded. The largest community for any given sample was found with Facebook. YouTube has been eliminated as for many samples (Dear Sir, StudyIQ), YouTube acts as a point of conversion rather than communication, and the same role is applicable to mobile applications for some other samples (SWAYAM). Hence, to avoid disparity of role, a common platform 'Facebook' was selected for the study.

Final Selection

Samples that registered highest frequency after eliminations were selected. Initially the non-relevant samples were eliminated according to the selection criteria and then, samples with highest frequency as per the responses were finally selected. To balance both groups, the top 8 government and 8 non-government samples were selected.

Table 3: Base Samples

Government (Group 1)	Non-Government (Group II)
AICTE	Byjus
Delhi University	Coursera
IGNOU	JagarnJosh
NCERT	Dear Sir
NPTEL	Meritnation
MHRD	StudyIQ
SWAYAM	Udemy
Digital India	Unacademy

Process of Data Collection and Analysis

The data has been collected using real time data extraction tool 'FanPage Karma'. The data for each sample was collected in two time periods separately.

Data Analysis

Growth Analysis

Table 4: Growth rates of samples

Sample	Community	Post	Reach	Like	Comment	Share	Post Interaction
DearSir	118.6143	147.619	296.1039	252.1711	3204.762	384.6897	78
Meritnation	107.4122	10.78431	76.12732	-45.7751	-29.0503	14.56876	37
Byjus	106	-37.6623	-1.05263	125.7525	-31.1475	-5.33708	42
DELHI UNIVERSITY	101	18.86792	84.61538	24.44444	161.2903	117.8138	38.28167
IGNOU	60	85.40146	193.4132	-15.5106	-62.9032	13.54765	22
NPTEL	58	51.92308	140.625	9.848485	-86.9347	47.92244	-1.21106
DIGITAL INDIA	52	100	222.2222	15.0592	40.98361	34.14634	15.95384
NCERT	42	-18.9189	28.84615	-9.03473	16.07251	3.018061	-12.7385
Unacademy	37.94397	700	0.12	71	42	77	179
SWAYAM	18	-34.0909	4.62963	200.9759	995.5357	234.3732	237.4925
AICTE	14	-36.3504	0.784314	55.39533	19.60622	-21.0585	47.0413
MHRD	-12	113.5593	211.6883	18.07072	202.4147	-49.9897	-2.56448
Udemy	-18.1874	233.3333	232.2034	2164.046	68	63.55932	1833.155
Coursera	-31.9099	-60.1882	-36.7418	-60.0606	-82.8803	-63.3686	-63.8544
JagarnJosh	-35.2667	-22.2222	22.72727	-23.6117	10.8229	18.87456	-20.5853
StudyIQ	-56.5243	34.85915	114.2857	-13.4646	-43.3546	-64.5442	-24.8411

all values are in percentage

The growth rate of the community was recorded to be positive for majority of the samples. The highest was obtained for DearSir (118.61%) and the lowest was obtained for StudyIQ (-56.52%). Four samples grew higher than 100% whereas five samples recorded negative growth rate. The average growth obtained for community size was 35.06%. The activity level was found to have increased for nine samples whereas six samples experienced decreased activity level. The highest was obtained for Unacademy (700%) and lowest was obtained for Coursera (-60%). The average growth rate for activity level obtained was 80.43%. Social media reach had grown for thirteen samples out of which four samples grew more than 200% whereas two samples showed negative growth rate. The highest was recorded for DearSir (296.10%) and the lowest was recorded for Coursera (-36.74%). The average growth rate obtained for 'Reach' was 99.41%. For engagement growth rate - like, comment and share - growth has been calculated separately. The growth for 'like' was found to be positive for nine samples whereas negative growth was obtained for six samples. The highest growth was obtained for Udemy (2164.04%) and the lowest was obtained for Coursera (-60.06%). The average growth rate obtained for 'like' was 173.08%. The growth rate obtained for 'comment' was positive for nine samples whereas six samples recorded negative growth rate. The highest growth was obtained for DearSir (3204.76%) and lowest was obtained for NPTEL (-86.93). The average growth rate for 'comment' was 276.57%. The growth rate obtained for 'share' was positive for eleven samples whereas five samples recorded negative growth. The highest was obtained for DearSir (384.68%) and negative was obtained for StudyIQ (64.54%). The average growth rate obtained was 50.32%. Post interaction grew for ten samples whereas negative rate was recorded for six samples. The highest growth was obtained for Udemy (1833.155%) and lowest was obtained for Coursera (-63.85%). The average growth rate obtained was 150.25%. The average score for growth rate obtained suggested that on average, all the elements had grown - comment (276.57%), like (173.08%) and post interaction (150.25%) grew above 100% whereas post and reach grew at 80.43% and 99.41% respectively. The lowest average growth rate was obtained for community (53.06%).

6.2 Performance Analysis

6.2.1 Correlation analysis for weighted score

Correlation analysis has been conducted in 4 segments considering the sample group and timeline of the data. Samples are grouped under government and non-government. Timeline has been considered under phase 1 and phase 2. The average correlation score for each sample has been calculated for determining its degree of impact on overall post interaction level.

Table 5: Correlation scores

Elements	Phase 1		Phase 2	
	Government	Non-Government	Government	Non-Government
Growth	0.85	0.92	0.93	0.95
Engagement	0.83	0.91	0.87	0.94
Activeness	0.79	0.83	0.83	0.88
Estimated Reach	0.71	0.82	0.8	0.85
Community Size	0.7	0.83	0.79	0.85
Share of Voice	0.62	0.69	0.69	0.72

The overall pattern of correlation between the factors and page interaction for both sample groups in either of the timeline remained consistent, but the relation between factors were revealed to be stronger in phase 2 compared to phase 1. Hence, the pattern obtained has been considered for formulating the weighted score for each element to conduct the overall performance analysis.

Correlation between Community Size Growth Rate and Engagement Rate

During phase 1, for non-government samples, the correlation score was 0.79 and for government samples, the correlation score was 0.75, whereas during phase 2, correlation score for non-government samples was recorded at 0.69 and for government samples, at 0.62.

Performance Rating

The performance score of each sample has been calculated and considered for positioning the samples. The overall analysis has been conducted for both phases.

Table 6: Performance scores

Sample	Phase 1	Phase 2	Difference
JagarnJosh	1	1	0
Digital India	0.730117	0.812654	0.082537
MHRD	0.781401	0.783577	0.002176
StudyIQ	0.67566	0.453573	-0.222087
DearSir	0.65789	0.375689	-0.282201
Delhi university	0.156963	0.28412	0.127157
Swayam	0.175641	0.18753	0.011889
Unacademy	0.082463	0.175616	0.093153
NCERT	0.154756	0.085911	-0.068845
NPTEL	0.154696	0.080767	-0.073929
Udemy	0.029572	0.037361	0.007789
Coursera	0.035174	0.037041	0.001867
IGNOU	0.154727	0.026327	-0.1284
Meritnation	0.004875	0.015626	0.010751
AICTE	0.154734	0.013725	-0.141009
Byju's	0.002741	0.003862	0.001121

Phase 1

The pattern obtained for group 1 was; MHRD>Digital India>Swayam>Delhi University> NCERT>AICTE>IGNOU>NPTEL and the pattern obtained for group 2 was; JagaranJosh>StudyIQ>Dear Sir>Unacademy>Coursera>Udemy>Meritnation.

Phase 2

The pattern obtained for group 1 was; Digital India>MHRD>Delhi University>Swayam>NCQERT>NPTEL>IGNOU>AICTE. The pattern obtained for group 2 was; JagarnJosh>StudyIQ>Dear Sir>Unacademy>Udemy>Coursera>Meritnation>Byju's.

Content Reception Analysis:

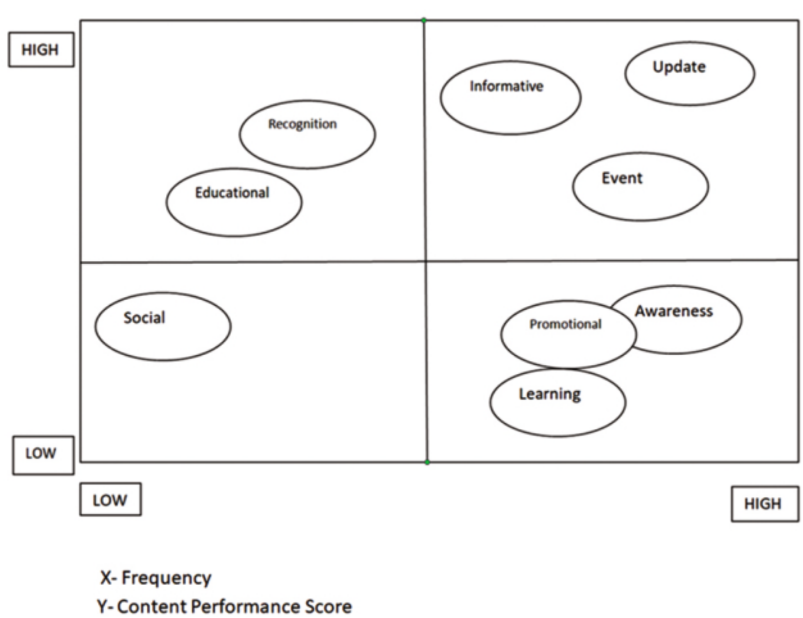
Table 7: Content Performance Score and Frequency

Content Type	Phase 1		Phase 2	
	Frequency	CPS	Frequency	CPS
Update	791	0.02146	1186	0.025478
Event	728	0.02143	1326	0.000541
Awareness	735	0.02032	843	0.014587
Promotional	672	0.01783	86	1.3E-09
Informative	652	0.00247	1270	0.036744
Recognition	434	0.000749	1566	0.002478
Educational	382	0.000429	1433	0.035621
Social	240	0.000371	1153	1.62E-05
Learning	665	1.45E-05	1604	0.037876

Initially, the content reception score was calculated for all samples separately under both the timelines and grouped under the following categories according to the theme of the post; Educational, Informative, Promotional, Learning, Awareness, Update, Event, Recognition, and Social. The result of the analysis has been represented in the following figures. The analysis is segregated according to phases.

Phase 1

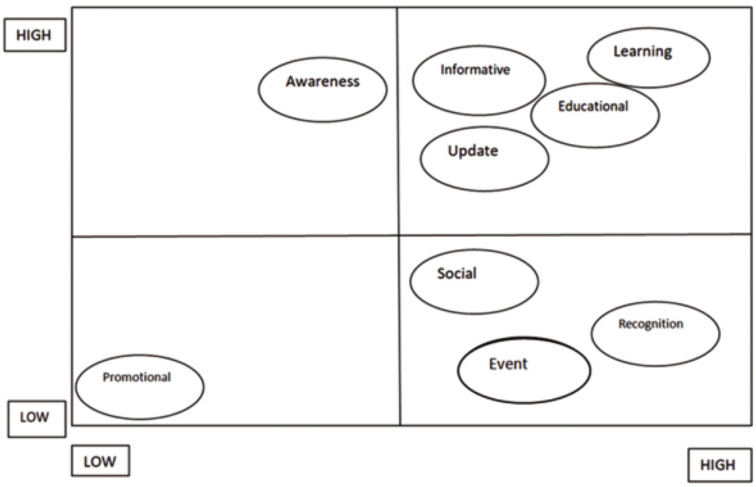
Figure 2: Phase 1 content performance matrix



During phase 1, the aggregate volume of posts was 5,299. The CPS score ranged between 0.0000145 (min) to 0.021456 (max). The highest score was obtained by an 'update' post from JagarnJosh whereas the lowest score was obtained by a 'learning' post from Unacademy. The CPS values were; update=0.02146, event=0.02143, awareness=0.02032, promotional=0.01783, informative=0.00247, recognition=0.000749, educational=0.000429, social=0.000371 and learning=0.0000145. The analysis revealed that post performance was highly impacted by frequency and estimated reach. 'Reach to Engagement' and 'Frequency to Engagement' have a high degree of negative impact if any post fails to generate the desired amount of engagement. Along with that, communicative size also impacts the overall performance. As a result, if any post with low frequency, small community and midrate reach generates large volume of engagement, it can result in better CPS values.

Phase 2

Figure 3: Phase 2 content performance matrix



X- Frequency
Y- Content Performance Score

During phase 2, the aggregate volume of posts was 9,952. The CPS score ranged between 0.00000162 (min) and 0.037876 (max). The highest score was obtained by a 'learning' post from 'Swayam' whereas the lowest score was obtained by a 'social' post from StudyIQ. A promotional post during the period couldn't pick up a significant amount of engagement despite having large community size although the frequency was extremely low. The CPS values were; learning=0.037876, informative=0.036744, educational=0.035621, update=0.025478, awareness=0.014587, recognition=0.002478, event=0.000541, social=0.0000162 and promotional=0.0000000013.

Regression analysis

Table 5: Correlation scores

Content Type	Phase 1	Phase 2
Update	0.7	0.72
Event	0.68	0.33
Awareness	0.6	0.68
Promotional	0.58	0.24
Informative	0.54	0.94
Recognition	0.42	0.45
Educational	0.41	0.8
Social	0.41	0.31
Learning	0.36	0.96

The results obtained from the content reception analysis suggest that a best fit model for page performance should include Learning, Informative, Update and Awareness. Hence, regression analysis has been conducted in two steps; firstly, taking independent variable (x) as learning (x_1), informative (x_2), update(x_3) and awareness (x_4) against dependent variable (y) page performance: each separately, and secondly, multiple logistic regression was conducted by considering content types as independent variable (x) and page performance score as dependent variable (y). The analysis has been conducted for both phase 1 and phase 2 separately.

Phase 1: The aggregate volume of posts for the phase was 5,299 out of which the aggregated share of independent variables was 2,310 (approximately 43% of the total posts).The adjusted R^2value (0.52) obtained revealed that independent variable can explain 52% of variation over dependent variable. In the next step, the model was expanded by considering all the content types as independent variable; the adjusted R^2value (0.37) obtained revealed that independent variable can only explain 37% of variation over dependent variable. The individual regression analysis has been conducted by taking Post Engagement as independent factor (X) and Page Performance Rating as dependent variable (Y). The individual adjusted R^2 values were; update=0.70, event=0.68, awareness=0.60, promotional=0.58, informative=0.54, recognition=0.42, educational=0.41, social=0.41 and learning=0.36. The overall analysis revealed that the model fitness decreases when all the content classes were considered as independent variable. The best fit model during the period consists of update, event, awareness and promotional.

Phase 2: The aggregate volume of posts for the phase was 9,952 out of which the aggregated share of independent variables was 6,170 (approximately 62% of the total posts). The adjusted R^2value (0.82) obtained revealed that independent variable can explain 82% of variation over dependent variable. In the next step, the model was expanded by considering all the content types as independent variable; the adjusted R^2value (0.22) obtained revealed that independent variable can only explain 22% of variation over dependent variable. The individual regression analysis has been conducted by taking Post Engagement as independent factor (X) and Page Performance Rating as dependent variable (Y). The individual adjusted R^2 values were; learning=0.96, informative=0.94, educational=0.80, update=0.72, awareness=0.68, recognition=0.45, event=0.33, social=0.31 and promotional=0.24.

Results

The growth analysis revealed that average growth rate for community size, reach, comment and share was higher for government samples whereas growth rate of 'post', 'like' and 'post interaction' was higher for non-government samples. The highest growth for government samples was recorded for 'comment' and for non-government samples was recorded for 'post interaction'. During phase 2, user interest level increased as activity growth rate for many samples like NPTEL (-37.6%), Coursera (-31.9%), JagarnJosh (-35.2%) were recorded negative but posts interaction still recorded positive growth of 42%, 273%, 47% respectively. Page performance analysis revealed that Digital India, Delhi University and NPTEL moved upward whereas MHRD, Swayam and AICTE moved downward in phase 2. The score of Digital India, Swayam, Delhi University increased whereas others decreased MHRD {0.78(II)<1(I)}, NCERT {0.08(II)<0.15(I)}, AICTE {0.01(II)<0.15(I)}, IGNOU {0.02(II)<0.15(I)} and NPTEL {0.08(II)<0,15(I)} even though samples have witnessed high growth in engagement. Irrespective of the movement of samples in the index, majority of the samples had improved engagement (volume). On the other side, non-government samples like Udemy moved upward and Coursera moved downward and Byju's got introduced at the last spot. The overall performance score lowered for two non-government samples; Dear Sir {0.37(II)<0.65(I)} and StudyIQ {0.45(II)<0.67(I)} despite having higher volume of page activity and user activity. The reason behind decline in the performance score is large inter-sample gap in activity level and overall community size. The score for all the samples increased except StudyIQ and DearSir as the scores are highly impacted by the activity level and community size. The change in content engagement pattern revealed user intent for communication to be more focused about 'learning' {0.037(II)>0.00001(I)} whereas the biggest fall was registered by 'promotional' post {0.000000001(II)<0.017(I)}. Apart from that, 'event' {0.0005(II)<0.021(I)} and 'awareness' {0.01(II)<0.02(I)} also registered lower scores. Content performance analysis also suggested that post performance has been highly impacted by frequency and estimated reach. Reach leads to Engagement and Frequency technically enhances Reach. Thus, Frequency and Reach have high degree of negative impact if they fail to achieve the desired level of engagement. The frequency of both learning and social post increased during phase 2. Learning post generated the desired level of engagement for a given 'Reach to Engagement' and 'Frequency to Engagement' ratio, but social post failed to achieve the desired engagement level despite having high frequency and reach. Learning post type featured in the low-high quadrant during phase 1 which suggests learning post was highly ignored by users during the period. The overall change in pattern of content performance score during phase 2 is highly affected by the activity pattern of the page. The frequency change in phase 2 for all content types is as follows; learning=939, recognition=1132, educational=1051, event=598, informative=618, update=395, social=913, awareness=108 and promotional=-586. The posting pattern suggests that pages focused towards recognition, educational, learning and social as these four content types registered the highest post frequency. The regression analysis further suggests the model fit for optimized content mix has better impact on performance when considered learning, informative, awareness and update as independent variables {adjusted R^2=0.52(I), 0.82(II)} compared against content mix of all content types as independent variable {adjusted R^2= 037(I), 0.22(II)}. The adjusted R^2 for optimized content mix increased whereas generic content mix decreased. The lockdown period has performed highly in terms of engagement including high value interactions, namely, comment, like and share. The performance of content types, namely, learning and informative have improved in comparison to other types of content. Another important insight the study revealed was - for any given timeline, the performance of learning {1604(II)>665(I}) and informative {1270(II)>652(I)} content was better in comparison to other content when considering the frequency. The study also suggests some relevant insights about user behaviour -users like to interact more with learning posts. The correlation between community growth rate and engagement declined over phase 2 for both the sample groups suggesting that existing user interaction has grown in phase 2. The pages have also changed their posting pattern as promotional activity fell to the least importance level and also failed to generate any significant level of engagement. Pages more focused on educational, recognition and learning posts actually resulted in better page performance.

Discussion and Implication

The study identified the pattern in content consumption through interaction and engagement. If the trend can be maintained after the lockdown with the right mix of content, the page performance can get better with the change in user behaviour mainly adopted during the lockdown. Further, the increase in average growth rate for all elements also suggests that user willingness to interact with learning content increased. The increase in adjusted R^2 value with optimized content mix suggests that engagement is highly specific as volume of page activity is spread over all content, but user activity is selective, which can be further explained with 'existing user' activity growth. Correlation between community growth and engagement declined during phase 2, which directly indicates that existing users have returned to the pages with the purpose of a meaningful interaction. The increase in learning and informative posts frequency and decrease in event and promotional activity indicates pages correctly estimated the user mood of engagement, but a few samples could not generate the desired volume of activity as compared to others due to content quality or any other technical effect. The pages which increased the frequency of learning, informative and awareness content significantly performed well when engagement was driven by existing users. Hence, the study concludes that the user is highly specific in selection of content type (learning, informative or education) and that reveals the user intent for subscriptions and purpose of interaction. The phase 2 engagement patterns were driven by existing users whereas phase I engagement patterns were more effective for community enlargement. Hence, the study suggests the pages must segregate content based on 'appeal' along with technical factors. The purpose of the content must be divided into two categories, namely, community enlargement (content targeted towards new users) and interaction enrichment (content dedicated for existing users). The assessment of the content's performance should be done periodically with content performance scores for each category and analyse the content ability to fulfil the purpose and make necessary changes as per requirement.

Generalization and Applicability

The findings of the study are primarily applicable to educational or learning related social media activities. The data sets used for the study were collected by generating real time interaction data of the sample units. The entire sample considered for the study was from India, but the findings of the study are applicable to other parts of the world as the study has been conducted with data sets of covid-19 period, which is a global phenomenon. Educational institutions were closed for months during the period across the world. The results obtained from the study may not be identical to other parts of the world, but the change in interaction pattern can be studied with the methodology used in the study for analysing posting strategy as samples have audience from different parts of the world like United States, United Kingdom, Australia, France, Canada, etc. Most of the countries across the world use edtech for various educational programs. Some the countries with similar government projects for digital education and learning are Afghanistan (Alternative Education Scheme for Persistence of 'Corona Virus), Argentina (Educ.ar), Austria (Moodle), Bangladesh, etc. These programs maintain Facebook pages for communication and promotional purposes. The findings of the study can be applied to any platform of any country with similar content and target audience.

Limitations and Scope for Future Research

The study has been conducted with data in the public domain, which is a constraint to measure actual reach leading to estimated engagement figures. Time length considered for the study was 5 months in aggregate starting from 1st January 2020 to 15th May 2020. That is even further broken down into two phases. Only one platform has been considered for the study to reduce the impact of data insufficiency. For future research studies, a wider time length and structured periodic analysis with admin level access of data can reveal more insights on engagement and its pattern. Along with that, the study doesn't cover individual performance analysis of the samples. Instead, it focuses on comparative equations for the analysis. The overall lower engagement for any specific sample cannot be answered with the findings of the study; rather, content quality assessment of the sample and posting strategy or technical assessment of the page at individual level has to be carried out for the same.

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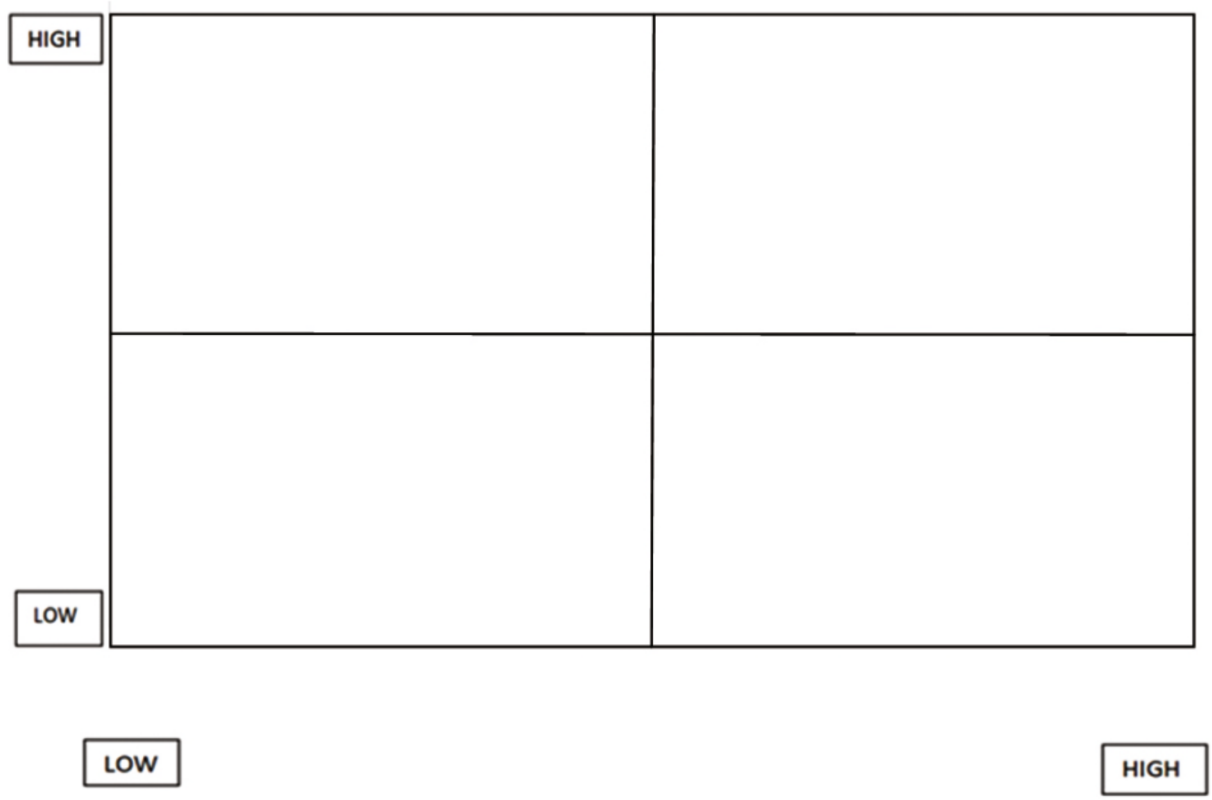
Annexure

Content Performance Matrix:



X-Frequency; Y- Content Performance Score

The matrix has 4 quadrants; Low-High (1), Low-Low (2), High-Low (3) and High-High (4).

Low-High : Out of User Interest Content Types

Low-Low : Uncertain Content Types

High-Low : Potential Content Types

High-High : Optimize Content Types

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