

# BHARATI VIDYAPEETH (DEEMED TO BE UNIVERSITY) INSTITUTE OF MANAGEMENT & RESEARCH, NEW DELHI 'A' GRADE UNIVERSITY STATUS AWARDED BY MHRD, GOVT, OF INDIA

CCREDITED WITH 'A+' GRADE BY NAAC

Events the terms

# REPORT ON FIVE DAYS ONLINE FACULTY DEVELOPMENT PROGRAMME (FDP) ON "QUALITATIVE RESEARCH ANALYSIS USING NVIVO

(October 25 - 29, 2021)



**Bharati Vidyapeeth (Deemed to be University) Institute of Management and Research (BVIMR), New Delhi conducted** FIVE DAYS ONLINE FACULTY DEVELOPMENT PROGRAMME (FDP) ON

Title: "QUALITATIVE RESEARCH ANALYSIS USING NVIVO"

Duration: OCTOBER 25-29, 2021 (Monday – Friday)

**Time**: 03:30 PM – 05:30 PM

Sessions : Three sessions will be conducted

# SESSION - 1 (Coding in NVIVO, Exploring word cloud and text search, Sentiment analysis and Social media analysis).

### **Contents:**

- What is nvivo?
- Why use nvivo?
- What file types are associated with nvivo?
- What version of nvivo does kent state currently use?
- How to frame Research Questions and objectives?
- Qualitative Analysis
- Types of Qualitative Analysis?
- Is there a version of nvivo for mac?
- How can I access NVivo?

### **SESSION - 2** (Publication in Scopus/ABDC for early researchers).

#### **Contents:**

- What is Scopus Preview?
- What is Scopus about?
- How do I register with Scopus and sign in ?
- How do I search for a document?
- Can I view articles on Scopus if I don't have subscribed access?
- Scopus Author Profile FAQs
- What can I do through My Scopus?

## **SESSION -3 (Practice Session on NVIVO)**

### **Summary**

NVIVO can be very useful for coding and finding connections. The challenge is to understand how you are putting your data into the system. Depending on your level of organization in your notes and transcripts, pictures, etc. The more NVIVO can assist you. They can be very helpful is answering questions, I would recommend learning about the system before you drive into your data analysis- as i feel there is small learning curve.

### **FEES:**

S.NO	FDP SUBJECT	FEES
1	QUALITATIVE RESEARCH ANALYSIS	<b>Rs.600</b>
	USING "NVIVO"	

Note: Participants were given choice to register in any module

## **Online Mode: MS Team**

## **Key Resource Person :**



## 1- Dr. Jaspreet Kaur

Dr. Jaspreet Kaur is an Associate professor at Pearl Academy. She has over 16 years of teaching experience in Marketing research. She has authored two books on Customer relationship Management and Service Marketing and has written many research papers in Scopus and ABDC journals.



2- Dr Navneet Gera, Associate Professor, BVIMR, New Delhi

Dr. Navneet Gera is Associate Professor in Bharati Vidyapeeth Institute of Management and Research, New Delhi. He did his doctorate from University of Rajasthan on 'Dollar Vs Euro in International Financial Markets'.



# 3-Dr. Ritika Malik , Assistant professor, BVIMR, New Delhi

Dr. Ritika Malik is Assistant Professor in Bharati Vidyapeeth Institute of Management and Research, New Delhi. She has 10 + years of experience in teaching, research and consulting in the area of General Management and 1 year corporate experience.

# **FDP Organisers:**



Dr. Pankaj Saini , Assistant Professor, BVIMR, A-4, Paschim Vihar , New Delhi
 (M) 9811960216, Email: pankaj.saini@bharatividyapeeth.edu



2 – Dr. Navneet Gera , Associate Professor, BVIMR, A-4, Paschim Vihar , New Delhi
(M) 9354185434 , Email : navneet.gera@bharatividyapeeth.edu



3 – Dr. Ritika Malik , Assistant Professor, BVIMR, A-4,Paschim Vihar , New Delhi
(M) -9650757675 , Email : ritika.malik@bharatividyapeeth.edu

#### **DAY WISE REPORT**

#### Day 1 (October 25, 2021 i.e. Monday)

The FDP was started at 03:30 PM and first address was given by organiser Dr. Ritika Malik, Assistant Professor, BVIMR, New Delhi . She said "Bharati Vidyapeeth, the parent body of Bharati Vidyapeeth (Deemed to be University),Pune, was established in 1964 by Hon'ble Dr. Patangraoji Kadam. It is having the privilege of 182 educational Institutions of academic excellence under its wings imparting education from pre-primary to research level. In recognition of its academic excellence, MHRD, Govt. of India granted the status of "Deemed to be University" on 26th April 1996 to a cluster of 12 Institutes of Bharati Vidyapeeth. It is now one of the few Universities which has under its umbrella diverse disciplines such as Management, Medicine, Law, Engineering, Science, Arts, Commerce, Pharmacy, Architecture and Social work etc. The University is accredited with 'A+' Grade (2017) by NAAC and awarded Category-I University status by UGC. It has been ranked 68<sup>th</sup> in Top 100 Universities in India by National Institutional Ranking Framework (NIRF) for 2021 year, BVIMR (Bharati vidyapeeth institute of management and Research ,New Delhi is a constituent unit of Bharati Vidyapeeth (Deemed to be University) Pune and is a premier Business School located in New Delhi and headed by our respected Director Dr. Yamini Agarwal."

### Dr. Ritika Malik then invited Dr. Jaspreet Kaur to take over the session.

Dr. Jaspreet then started the session with the introduction of research under which she has covered the types of Research and Types of data. She gave the brief information about the same. After this, Dr. Jaspreet has provided us with the brief knowledge of the Research Process along with the details about what exactly is the review of NVIVO and how can it be beneficial to all of us and what exactly is the process that goes along the way while using it. Under the same Mam has given the brief details about the installation of NVIVO, registration and how to begin with it. She explained how we can analyse our qualitative data. With this Dr, Jaspreet has concluded the Day-1 session after having the Q n A session.



Pic 1: Dr. Ritika Malik giving the introduction of University and FDP.



**Pic 2:** Dr. Jaspreet kaur taking her session on Coding in NVIVO, Exploring word cloud and text search, Sentiment analysis and Social media analysis.

## Day 2 ( October 26, 2021 i.e. Tuesday )

The FDP was started at 03:30 PM and Jaspreet kaur started her session for the Day-2 with introduction and highlighted the following points

In NVivo for Windows, you can "undock" the views of open sources, nodes, queries, or other project items by right-clicking on the item's tab and selecting Undock. This will open the item in its own viewer window. This is particularly useful if you have dual monitors: you can open a data source on one monitor, and have the node view on the other.

**Choosing between Word or PDF formats?** Word and plain text files are easier to code in NVivo than PDFs

In general, it is easier to code plain text and Word documents than it is to code PDFs. Automated word detection (such as word frequency and text search queries) also work better on plain text and Word documents than they do on PDFs. If you have a choice between the two formats and your analysis only requires the text, choose plain text.

**Headers, footers, and page numbers** in Word docs are hidden when viewing the file in NVivo If your Word source document has headers, footers, and page numbers, they will be hidden when the document is imported into NVivo. This makes it easier to code long passages of text. This is NOT true of PDFs: headers, footers, and page numbers cannot be ignored, and can interfere with coding sentences or paragraphs that carry over a page.



Pic 3: Dr. Jaspreet kaur taking her session on Types of Qualitative Research

### Day 3 (October 27, 2021 i.e. Wednesday)

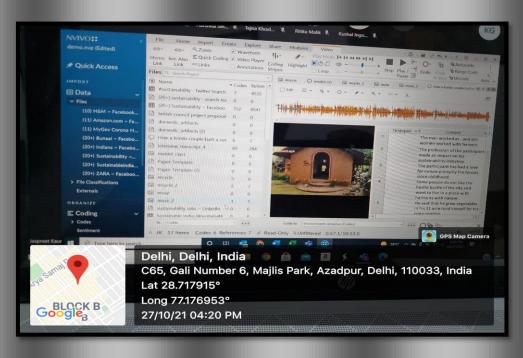
The FDP was started at 03:30 PM and first address was given by organiser Dr. Ritika Malik ,Assistant Professor, BVIMR, New Delhi .After giving brief introduction about Bharti Vidyapeeth and BVIMR, New Delhi . She then invited Dr Jaspreet kaur to take over the session. **Need line numbers? Save your source as a PDF** 

If you have a Microsoft Word document with line numbers that you want to import into NVivo 10, those line numbers will not be visible in NVivo. If you wish to be able to see the line numbers, save the Word document as a PDF, and import that PDF into NVivo. Note that you will be able to see the line numbers when viewing the source, but not when viewing coded content in a node. (May 2015)

# To avoid corrupting your NVivo project files, do not store them on a network drive, external hard drive, or cloud-synced directory

Because of how NVivo saves project data, it is generally not recommended to keep your NVivo project file (\*.nvp or \*.nvpx) on a network drive, on a folder that is synced to the cloud, or on an external hard drive or USB drive. If your connection to a network drive or external drive is severed at any time while your NVivo project is still open, the file will become corrupted.

- If you want to keep your NVivo project file on a network drive, change the "Update projects on networks drives" setting to On save.
- If you are keeping your project file in a folder that is synced to a cloud storage service (such as Dropbox, Google Drive, Box, etc.), QSR recommends pausing syncing while you have the project open.



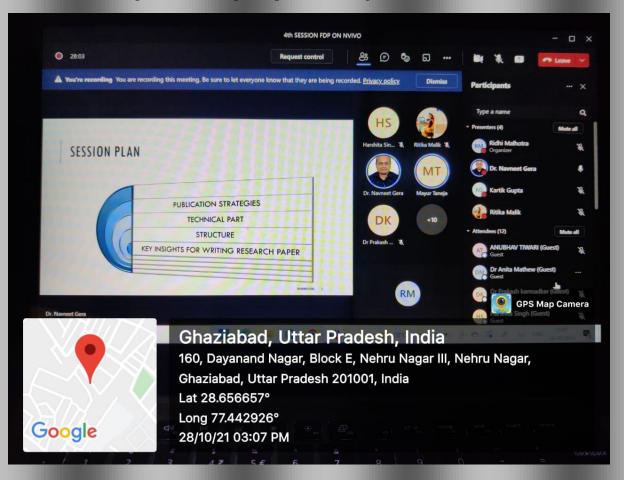


### Day 4 ( October 28,2021 i.e. Thursday )

The FDP was started at 3 pm and Dr. Navneet Gera started his session for 4<sup>th</sup> Day of the FDP. Scopus uniquely combines a comprehensive, expertly curated abstract and citation database with enriched data and linked scholarly literature across a wide variety of disciplines.

Scopus quickly finds relevant and authoritative research, identifies experts and provides access to reliable data, metrics and analytical tools. Be confident in progressing research, teaching or research direction and priorities — all from one database and with one subscription..





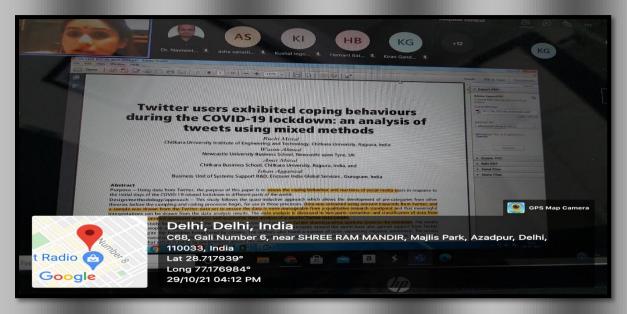
### Pic 5: Group Picture of all participants attending the FDP.

#### Day 5 (October 29,2021 i.e. Friday)

The FDP was started at 3:00 pm Dr. Ritika malik took session on detailed steps about how to import social media data through N- capture. Dr. Ritika Malik briefed the participants about Twitter N – capture data using key words social distancing, lockdown etc and briefed about sentiment analysis, thematic analysis using those tweets also summed up the session by taking all querries from the participants.

Analysis of tweets using mixed methods       Analysis of tweets       <	Image: Strain and addition of the set sentence of the set sentence of the set sentence of the set set set set of the set set set set set set set set set se	Analysis of tweets using mised methods       Image: 1 mised methods       Image: 1 mised methods       Image: 1 mised methods       Image: 1 mised methods         Analysis of tweets using mised methods       Image: 1 mised methods       Image: 1 mised methods       Image: 1 mised methods       Image: 1 mised methods         Mathematic And Water And		FDP NVIVO
Dr. Novneet.       Kushal Ingo.       asha sanath *       Ritka Adga *       Rajakumar, *         Analysis of tweets using mixed methods Rack Market. Brasen Almend. Amit Market and Takan Ageanedt       Information Discovery and Delivery         Table 1 Frequency count of themes within each sentiment-based category       Information Discovery and Delivery         S. No.       Theme Negative Tweets       Positive Tweets       Neutral Topological Count         1       Freedomark distress       18         3       Freedomark distress       18         4       Freedomark distress       18         5       Government and lasters       18         6       Freedomark and Justee       9         7       Freedomark and Justee       9         8       Government and lesterss       18         1       Freedomark and Justee       9         1       Freedomark and Justee       9         2       Freedomark and Justee       9         3       Government and lestership       30         3       Government and lestership       30         3       Freedomark and Justee       6         3       Freedomark and Justee       6         3       Freedomark andescenship       30	Dr. Navneet.       Kushal Ingo.       asha sanath.       Ritka Agga.       Rajakumar.       Rajakumar.         Analysis of tweets using mixed methods       Information Discovery and Delivery         Table 1       Free Market.       Information Discovery and Delivery         Table 3       Theme       No.         S. No.       Theme       Negative Tweets       Positive Tweets       Neutral         1       Emotional distress       18       18         3       Kolence, theft and abuse       9       1         4       Emotional distress       18       18         5       Uncomptoyment and kedership       30       35       33         6       Terretaingent       33       33       33         5       Uncomptoyment and kedership       30       35       33         6       Terretaingent       33       33       33         5       Uncomptoyment and kedership       30       35       33         6       Terretaingent       33       33       33         6       Terretaingent       33       33       33         6       Terretaingent       33       33       33         6       Terretaingent <td< th=""><th>Dr. Navneet.     Kushal Ingo.     asha sanath.     Ritika Agga.     Rijakumar.       Analysis of tweets using mixed methods     Information Discovery and Delivery       Rent Merid.     Frankis of tweets using mixed methods       Rent Merid.     Frankis of tweets using mixed methods.       So in the method distress     18       So in the method distress     18       Violence.     14       Frankis of tweets within each sentiment-based category     Foundation Discovery and Delivery       Importance     Repart of the methods.     Neutral Twee       Importance     10     Count       Importance     13     Sereas       Importance     14     Sereas       Importance     13     Sereas       Importance     13     Sereas       Importance     14     Sereas       Importance     14     Sereas</th><th></th><th></th></td<>	Dr. Navneet.     Kushal Ingo.     asha sanath.     Ritika Agga.     Rijakumar.       Analysis of tweets using mixed methods     Information Discovery and Delivery       Rent Merid.     Frankis of tweets using mixed methods       Rent Merid.     Frankis of tweets using mixed methods.       So in the method distress     18       So in the method distress     18       Violence.     14       Frankis of tweets within each sentiment-based category     Foundation Discovery and Delivery       Importance     Repart of the methods.     Neutral Twee       Importance     10     Count       Importance     13     Sereas       Importance     14     Sereas       Importance     13     Sereas       Importance     13     Sereas       Importance     14     Sereas       Importance     14     Sereas		
Dr. Novneet.       Kushal Ingo.       asha sanath *       Ritka Adga *       Rajakumar, *         Analysis of tweets using mixed methods Rack Market. Brasen Almend. Amit Market and Takan Ageanedt       Information Discovery and Delivery         Table 1 Frequency count of themes within each sentiment-based category       Information Discovery and Delivery         S. No.       Theme Negative Tweets       Positive Tweets       Neutral Topological Count         1       Freedomark distress       18         3       Freedomark distress       18         4       Freedomark distress       18         5       Government and lasters       18         6       Freedomark and Justee       9         7       Freedomark and Justee       9         8       Government and lesterss       18         1       Freedomark and Justee       9         1       Freedomark and Justee       9         2       Freedomark and Justee       9         3       Government and lestership       30         3       Government and lestership       30         3       Freedomark and Justee       6         3       Freedomark and Justee       6         3       Freedomark andescenship       30	Dr. Navneet.       Kushal Ingo.       asha sanath.       Ritka Agga.       Rajakumar.       Rajakumar.         Analysis of tweets using mixed methods       Information Discovery and Delivery         Table 1       Free Market.       Information Discovery and Delivery         Table 3       Theme       No.         S. No.       Theme       Negative Tweets       Positive Tweets       Neutral         1       Emotional distress       18       18         3       Kolence, theft and abuse       9       1         4       Emotional distress       18       18         5       Uncomptoyment and kedership       30       35       33         6       Terretaingent       33       33       33         5       Uncomptoyment and kedership       30       35       33         6       Terretaingent       33       33       33         5       Uncomptoyment and kedership       30       35       33         6       Terretaingent       33       33       33         6       Terretaingent       33       33       33         6       Terretaingent       33       33       33         6       Terretaingent <td< th=""><th>Dr. Navneet.     Kushal Ingo.     asha sanath.     Ritika Agga.     Rijakumar       Analysis of tweets using mixed methods     Information Discovery and Delivery       Rent Merid.     Frankis of tweets using mixed methods       So in the method distress     18       So in the method distress     18       Violence.     14       Frankis of tweets within each sentiment-based category     Formation Discovery and Deliver       Intermethod distress     18       Violence.     19       Violence.     19       Stream of hump by ment     10       Stream of the methods     13       Mixed house     13       Mixed house     13       Stream of the methods     13   &lt;</th><th></th><th></th></td<>	Dr. Navneet.     Kushal Ingo.     asha sanath.     Ritika Agga.     Rijakumar       Analysis of tweets using mixed methods     Information Discovery and Delivery       Rent Merid.     Frankis of tweets using mixed methods       So in the method distress     18       So in the method distress     18       Violence.     14       Frankis of tweets within each sentiment-based category     Formation Discovery and Deliver       Intermethod distress     18       Violence.     19       Violence.     19       Stream of hump by ment     10       Stream of the methods     13       Mixed house     13       Mixed house     13       Stream of the methods     13   <		
Dr. Novneet.       Kushal Ingo.       asha sanath *       Ritka Adga *       Rajakumar, *         Analysis of tweets using mixed methods Rack Market. Brasen Almend. Amit Market and Takan Ageanedt       Information Discovery and Delivery         Table 1 Frequency count of themes within each sentiment-based category       Information Discovery and Delivery         S. No.       Theme Negative Tweets       Positive Tweets       Neutral Topological Count         1       Freedomark distress       18         3       Freedomark distress       18         4       Freedomark distress       18         5       Government and lasters       18         6       Freedomark and Justee       9         7       Freedomark and Justee       9         8       Government and lesterss       18         1       Freedomark and Justee       9         1       Freedomark and Justee       9         2       Freedomark and Justee       9         3       Government and lestership       30         3       Government and lestership       30         3       Freedomark and Justee       6         3       Freedomark and Justee       6         3       Freedomark andescenship       30	Dr. Navneet.       Kushal Ingo.       asha sanath.       Ritka Agga.       Rajakumar.       Rajakumar.         Analysis of tweets using mixed methods       Information Discovery and Delivery         Table 1       Free Market.       Information Discovery and Delivery         Table 3       Theme       No.         S. No.       Theme       Negative Tweets       Positive Tweets       Neutral         1       Emotional distress       18       18         3       Kolence, theft and abuse       9       1         4       Emotional distress       18       18         5       Uncomptoyment and kedership       30       35       33         6       Terretaingent       33       33       33         5       Uncomptoyment and kedership       30       35       33         6       Terretaingent       33       33       33         5       Uncomptoyment and kedership       30       35       33         6       Terretaingent       33       33       33         6       Terretaingent       33       33       33         6       Terretaingent       33       33       33         6       Terretaingent <td< th=""><th>Dr. Navneet.     Kushal Ingo.     asha sanath.     Ritika Agga.     Rijakumar       Analysis of tweets using mixed methods     Information Discovery and Delivery       Rent Merid.     Frankis of tweets using mixed methods       So in the method distress     18       So in the method distress     18       Violence.     14       Frankis of tweets within each sentiment-based category     Formation Discovery and Deliver       Intermethod distress     18       Violence.     19       Violence.     19       Stream of hump by ment     10       Stream of the methods     13       Mixed house     13       Mixed house     13       Stream of the methods     13   &lt;</th><th></th><th></th></td<>	Dr. Navneet.     Kushal Ingo.     asha sanath.     Ritika Agga.     Rijakumar       Analysis of tweets using mixed methods     Information Discovery and Delivery       Rent Merid.     Frankis of tweets using mixed methods       So in the method distress     18       So in the method distress     18       Violence.     14       Frankis of tweets within each sentiment-based category     Formation Discovery and Deliver       Intermethod distress     18       Violence.     19       Violence.     19       Stream of hump by ment     10       Stream of the methods     13       Mixed house     13       Mixed house     13       Stream of the methods     13   <		
Dr. Novneet.       Kushal Ingo.       asha sanath *       Ritka Adga *       Rajakumar, *         Analysis of tweets using mixed methods Rack Market. Brasen Almend. Amit Market and Takan Ageanedt       Information Discovery and Delivery         Table 1 Frequency count of themes within each sentiment-based category       Information Discovery and Delivery         S. No.       Theme Negative Tweets       Positive Tweets       Neutral Topological Count         1       Freedomark distress       18         3       Freedomark distress       18         4       Freedomark distress       18         5       Government and lasters       18         6       Freedomark and Justee       9         7       Freedomark and Justee       9         8       Government and lesterss       18         1       Freedomark and Justee       9         1       Freedomark and Justee       9         2       Freedomark and Justee       9         3       Government and lestership       30         3       Government and lestership       30         3       Freedomark and Justee       6         3       Freedomark and Justee       6         3       Freedomark andescenship       30	Dr. Navneet.       Kushal Ingo.       asha sanath.       Ritka Agga.       Rajakumar.       Rajakumar.         Analysis of tweets using mixed methods       Information Discovery and Delivery         Table 1       Free Market.       Information Discovery and Delivery         Table 3       Theme       No.         S. No.       Theme       Negative Tweets       Positive Tweets       Neutral         1       Emotional distress       18       18         3       Kolence, theft and abuse       9       1         4       Emotional distress       18       18         5       Uncomplexity memory       3       3         6       Free transmitting       1       1         7       Emotional distress       18       1         1       Emotional distress       18       1         1       Emotional distress       13       1         3       Violence, theft and abuse       1       1         4       Government and kadeship       30       35       3         5       Uncomplexity       13       14       14         6       Free training       13       14       15         6       Free training	Dr. Navneet.     Kushal Ingo.     asha sanath.     Ritika Agga.     Rijakumar       Analysis of tweets using mixed methods     Information Discovery and Delivery       Rent Merid.     Frankis of tweets using mixed methods       So in the method distress     18       So in the method distress     18       Violence.     14       Frankis of tweets within each sentiment-based category     Formation Discovery and Deliver       Intermethod distress     18       Violence.     19       Violence.     19       Stream of hump by ment     10       Stream of the methods     13       Mixed house     13       Mixed house     13       Stream of the methods     13   <		
Dr. Novneet.       Kushal Ingo.       asha sanath *       Ritka Adga *       Rajakumar, *         Analysis of tweets using mixed methods Rack Market. Brasen Almend. Amit Market and Takan Ageanedt       Information Discovery and Delivery         Table 1 Frequency count of themes within each sentiment-based category       Information Discovery and Delivery         S. No.       Theme Negative Tweets       Positive Tweets       Neutral Topological Count         1       Freedomark distress       18         3       Freedomark distress       18         4       Freedomark distress       18         5       Government and lasters       18         6       Freedomark and Justee       9         7       Freedomark and Justee       9         8       Government and lesterss       18         1       Freedomark and Justee       9         1       Freedomark and Justee       9         2       Freedomark and Justee       9         3       Government and lestership       30         3       Government and lestership       30         3       Freedomark and Justee       6         3       Freedomark and Justee       6         3       Freedomark andescenship       30	Dr. Navneet.       Kushal Ingo.       asha sanath.       Ritka Agga.       Rajakumar.       Rajakumar.         Analysis of tweets using mixed methods       Information Discovery and Delivery         Table 1       Free Market.       Information Discovery and Delivery         Table 3       Theme       No.         S. No.       Theme       Negative Tweets       Positive Tweets       Neutral         1       Emotional distress       18       18         3       Kolence, theft and abuse       9       1         4       Emotional distress       18       18         5       Uncomplexity memory       3       3         6       Free transmitting       1       1         7       Emotional distress       18       1         1       Emotional distress       18       1         1       Emotional distress       13       1         3       Violence, theft and abuse       1       1         4       Government and kadeship       30       35       3         5       Uncomplexity       13       14       14         6       Free training       13       14       15         6       Free training	Dr. Navneet.     Kushal Ingo.     asha sanath.     Ritika Agga.     Rajakumar,     Rejakumar,       Analysis of tweets using mixed methods     Information Discovery and Delivery       Analysis of tweets using mixed methods     Information Discovery and Delivery       Rate Mark Brand, Amic Mark and Than Aggreed     Information Discovery and Delivery       Table 1 Frequency count of themes within each sentiment-based category     Positive Tweets     Neutral Tweets       1     Emotional distress     18       3     Volonce, theft and abuse     9       4     Emotional distress     18       5     Government and kaderschip     30       6     Government and kaderschip     30       6     Sacali Number 6, near SHREEE RAM MANDIR, Majlis Park,       7     Long 77.1769664°       9     29/10/21 04:34 PM		AS RA MR
Analysis of tweets using mixed methods     Information Discovery and Delivery       Ruch Afferid, Praem Almond, Amit Mand and Isham Agaared     Information Discovery and Delivery       Table 1 Frequency count of themes within each sentiment-based category     Positive Tweets     Positive Tweets       S. No.     Theme     Negative Tweets     Positive Tweets       Image: Sentiment Amit Afferd and Isham Agaared     Count     Count       Image: Sentiment Amit Afferd and Isham Agaared     Count     Count       Image: Sentiment Afferd and Isham Agaared     Sentiment Afferd and Isham Agaared     Neutral       Image: Sentiment Afferd and Isham Agaared     Count     Count       Image: Sentiment Afferd and Isham Agaared     Sentiment Afferd and Isham Agaared     Sentiment Afferd and Isham Agaared       Image: Sentiment Afferd and Isham Agaared     Sentiment Afferd and Isham Agaared     Sentiment Afferd and Isham Agaared       Image: Sentiment Afferd and Isham Agaared     Sentiment Afferd and Isham Agaared     Sentiment Afferd Agaared       Image: Sentiment Afferd and Isham Agaared     Sentiment Afferd Agaared     Sentiment Afferd Agaared       Image: Sentiment Afferd and Isham Agaared     Sentiment Afferd Agaared     Sentiment Afferd Agaared       Image: Sentiment Afferd Agaared     Sentiment Afferd Agaared     Sentiment Afferd Agaared       Image: Sentiment Afferd Agaared     Sentiment Afferd Agaared     Sentiment Afferd Agaared    <	Analysis of tweets using mixed methods     Information Discovery and Delivery       Richard Mixed, Watern Almad, Anna Marad and Fuhan, Aggareed     Information Discovery and Delivery       Table 1 Frequency count of themes within each sentiment-based category     Positive Tweets     Positive Tweets       5 No.     Temptional distress     18       6 Temptional distress     18       7     Emotional distress     18       8     Government and loadership     30       9     Government and loadership     30       9     Government and loadership     31       10     Emotional distress     19       10     Emotional distress     10       11     Emotional distress     10       12     Emotional distress     10       13     Emotional distress     10       14     Emotional distress     10       15     Government and loadership     33       16     Emotional	Analysis of tweets using mixed methods Rich Maria, Brann Ahmed, Amit Maria and Ehan Ageneed Table 1 Frequency count of themes within each sentiment-based category 5. No. Theme Negative Tweets Positive Tweets Neutral Tw Count		
Analysis of tweets using mixed methods     Information Discovery and Delivery       Ruch Afferid, Praem Almond, Amit Mand and Isham Agaared     Information Discovery and Delivery       Table 1 Frequency count of themes within each sentiment-based category     Positive Tweets     Positive Tweets       S. No.     Theme     Negative Tweets     Positive Tweets       Image: Sentiment Amit Afferd and Isham Agaared     Count     Count       Image: Sentiment Amit Afferd and Isham Agaared     Count     Count       Image: Sentiment Afferd and Isham Agaared     Sentiment Afferd and Isham Agaared     Neutral       Image: Sentiment Afferd and Isham Agaared     Count     Count       Image: Sentiment Afferd and Isham Agaared     Sentiment Afferd and Isham Agaared     Sentiment Afferd and Isham Agaared       Image: Sentiment Afferd and Isham Agaared     Sentiment Afferd and Isham Agaared     Sentiment Afferd and Isham Agaared       Image: Sentiment Afferd and Isham Agaared     Sentiment Afferd and Isham Agaared     Sentiment Afferd Agaared       Image: Sentiment Afferd and Isham Agaared     Sentiment Afferd Agaared     Sentiment Afferd Agaared       Image: Sentiment Afferd and Isham Agaared     Sentiment Afferd Agaared     Sentiment Afferd Agaared       Image: Sentiment Afferd Agaared     Sentiment Afferd Agaared     Sentiment Afferd Agaared       Image: Sentiment Afferd Agaared     Sentiment Afferd Agaared     Sentiment Afferd Agaared    <	Analysis of tweets using mixed methods     Information Discovery and Delivery       Richard Mixed, Watern Almad, Anna Marad and Fuhan, Aggareed     Information Discovery and Delivery       Table 1 Frequency count of themes within each sentiment-based category     Positive Tweets     Positive Tweets       5 No.     Temptional distress     18       6 Temptional distress     18       7     Emotional distress     18       8     Government and loadership     30       9     Government and loadership     30       9     Government and loadership     31       10     Emotional distress     19       10     Emotional distress     10       11     Emotional distress     10       12     Emotional distress     10       13     Emotional distress     10       14     Emotional distress     10       15     Government and loadership     33       16     Emotional	Analysis of tweets using mixed methods Rich Marid, Brander Amit Marid and Ethan Agenred Table 1 Frequency count of themes within each sentiment-based category 5. No. Theme Negative Tweets Positive Tweets Neutral Tw Count Coun	Dr. Navneet 2 Kushal Ingo	
Reach Atterat, IP arawn Atterat, and Atterat and Tables Ageneration     Interferences       Table 1 Frequency count of themes within each sentiment-based category     S. No.     Negative Tweets     Positive Tweets       S. No.     Theme     Negative Tweets     Count     Count       I     Emotional distress     18       Sarcosm     15       Violence, theft and abuse     15       I     Emotional distress     18       Sarcosm     15       I ferreduction and theme workers     15       I ferreductions     15       I ferreductions     15       I ferreductions     13       I ferreductions     14       I ferreductions     13       I ferreductions     14       I ferreductions     14       I ferreductions     14       I ferreductions     15       I ferreductions     14       I ferreductions     15       I ferreductions     14       I ferreductions     15       I ferreductions     14       I fereductions     15       I	Review Altered, Altered and Phase Algebrased       Information Distance Algebrased       Information Distance Algebrased       Table 1 Frequency count of themes within each sentiment-based category       S. No.       Theme       Negative Tweets       Count	Rever Aftered, Hirade Aftered and Ethical Aggeneral     Interference       Table 1 Frequency count of themes within each sentiment-based category       S. No.     Theme       Rest Aftered and Ethical Aggeneral       Image: Source of themes within each sentiment-based category       S. No.     Theme       Rest Aftered and Ethical Aggeneral       Image: Source of the sentiment based category       Source of the sentiment based category       Image: Source of the sentime	Christaniecu 🛠 Kushai Ingo 🛠 a	isna sanath 来 Ritika Agga 来 Rajakumar, 楽
Reach Atterat, IP arawn Atterat, and Atterat and Tables Ageneration     Interferences       Table 1 Frequency count of themes within each sentiment-based category     S. No.     Negative Tweets     Positive Tweets       S. No.     Theme     Negative Tweets     Count     Count       I     Emotional distress     18       Sarcosm     15       Violence, theft and abuse     15       I     Emotional distress     18       Sarcosm     15       I ferreduction and theme workers     15       I ferreductions     15       I ferreductions     15       I ferreductions     13       I ferreductions     14       I ferreductions     13       I ferreductions     14       I ferreductions     14       I ferreductions     14       I ferreductions     15       I ferreductions     14       I ferreductions     15       I ferreductions     14       I ferreductions     15       I ferreductions     14       I fereductions     15       I	Review Altered, Altered and Phase Algebrased       Information Distance Algebrased       Information Distance Algebrased       Table 1 Frequency count of themes within each sentiment-based category       S. No.       Theme       Negative Tweets       Count	Rever Aftered, Hirade Aftered and Ethical Aggeneral     Interference       Table 1 Frequency count of themes within each sentiment-based category       S. No.     Theme       Rest Aftered and Ethical Aggeneral       Image: Source of themes within each sentiment-based category       S. No.     Theme       Rest Aftered and Ethical Aggeneral       Image: Source of the sentiment based category       Source of the sentiment based category       Image: Source of the sentime		
Reach Atterat, IP arawn Atterat, and Atterat and Tables Ageneration     Interferences       Table 1 Frequency count of themes within each sentiment-based category     S. No.     Negative Tweets     Positive Tweets       S. No.     Theme     Negative Tweets     Count     Count       I     Emotional distress     18       Sarcosm     15       Violence, theft and abuse     15       I     Emotional distress     18       Sarcosm     15       I ferreduction and theme workers     15       I ferreductions     15       I ferreductions     15       I ferreductions     13       I ferreductions     14       I ferreductions     13       I ferreductions     14       I ferreductions     14       I ferreductions     14       I ferreductions     15       I ferreductions     14       I ferreductions     15       I ferreductions     14       I ferreductions     15       I ferreductions     14       I fereductions     15       I	Resets     Interference       Table 1 Frequency count of themes, within each sentiment-based category       S. No.     Theme       2     Surcess       3     Surcess       4     Emotional distress       5     16       5     Surcess       6     Frequency count of themes within each sentiment-based category       7     Emotional distress       3     Surcess       4     Surcess       5     Frequency count of themes within each sentiment-based category       6     Frequency count of themes within each sentiment-based category       7     Emotional distress       3     Violence, theft and abuse       9     Frequency count of themes workers       6     Frequency count of kadeship       7     B       8     Thesite workers       9     Government and kadeship       9     Government and kadeship       9     Government and kadeship       9     Born tairing       9     Government and kadeship       9     Government and	Rever Aftered, Hirade, Annie Aftered and Ethons, Aggeneral     Individual and Ethons, Aggeneral       Table 1 Frequency count of themes within each sentiment-based category     Positive Tweets     Positive Tweets       S. No.     Theme     Regative Tweets     Positive Tweets       S. No.     Theme     Regative Tweets     Positive Tweets       Strength     15     Strength     Regative Tweets       Valorice, theft and abuse     15     Strength     Regative Tweets       Valorice, theft and abuse     15     Strength     Regative Tweets       Valorice, theft and abuse     15     Strength     Regative Tweets       Strength     Regative Tweets     Regative Tweets     Regative Tweets       Valorice, theft and abuse     15     Strength     Regative Tweets       Strength     16     Strength     Regative Tweets     Regative Tweets       Valorice, theft and abuse     15     Strength     Regative Tweets     Regative Tweets       B. Headthcare workers     16     16     Regative Tweets     Regative Tweets       B. Headthcare workers     13     10     13     Regative Tweets       B. Headthcare workers     10     10     15     10       B. Headthcare Workers     10     10     15     10       B. Son/110033, India		
Reach Atterat, IP arawn Atterat, and Atterat and Tables Ageneration     Interferences       Table 1 Frequency count of themes within each sentiment-based category     S. No.     Negative Tweets     Positive Tweets       S. No.     Theme     Negative Tweets     Count     Count       I     Emotional distress     18       Sarcosm     15       Violence, theft and abuse     15       I     Emotional distress     18       Sarcosm     15       I ferreduction and theme workers     15       I ferreductions     15       I ferreductions     15       I ferreductions     13       I ferreductions     14       I ferreductions     13       I ferreductions     14       I ferreductions     14       I ferreductions     14       I ferreductions     15       I ferreductions     14       I ferreductions     15       I ferreductions     14       I ferreductions     15       I ferreductions     14       I fereductions     15       I	Recht Affareit, Waren Afhaneit, Amit Affareit amf Erham Aggenereit     Interferent States       Table 1 Frequency count of themes within each sentiment-based category       S. No.     Theme     Negative Tweets       2     Sarcosm     18       3     Sarcosm     15       4     Sarcosm     15       5     Precautions     13       6     Precautions     13       7     Sarcosm     16       8     Healthcare workers     13       9     Government and leakership     30     35       9     Gover	Rever Aftered, Hirade, Annie Aftered and Ethons, Aggeneral     Individual and Ethons, Aggeneral       Table 1 Frequency count of themes within each sentiment-based category     Positive Tweets     Positive Tweets       S. No.     Theme     Regative Tweets     Positive Tweets       S. No.     Theme     Regative Tweets     Positive Tweets       Strength     15     Strength     Regative Tweets       Valorice, theft and abuse     15     Strength     Regative Tweets       Valorice, theft and abuse     15     Strength     Regative Tweets       Valorice, theft and abuse     15     Strength     Regative Tweets       Strength     Regative Tweets     Regative Tweets     Regative Tweets       Valorice, theft and abuse     15     Strength     Regative Tweets       Strength     16     Strength     Regative Tweets     Regative Tweets       Valorice, theft and abuse     15     Strength     Regative Tweets     Regative Tweets       B. Headthcare workers     16     16     Regative Tweets     Regative Tweets       B. Headthcare workers     13     10     13     Regative Tweets       B. Headthcare workers     10     10     15     10       B. Headthcare Workers     10     10     15     10       B. Son/110033, India		
Reach Atterat, IP arawn Atterat, and Atterat and Tables Ageneration     Interferences       Table 1 Frequency count of themes within each sentiment-based category     S. No.     Negative Tweets     Positive Tweets       S. No.     Theme     Negative Tweets     Count     Count       I     Emotional distress     18       Sarcosm     15       Violence, theft and abuse     15       I     Emotional distress     18       Sarcosm     15       I ferreduction and theme workers     15       I ferreductions     15       I ferreductions     15       I ferreductions     13       I ferreductions     14       I ferreductions     13       I ferreductions     14       I ferreductions     14       I ferreductions     14       I ferreductions     15       I ferreductions     14       I ferreductions     15       I ferreductions     14       I ferreductions     15       I ferreductions     14       I fereductions     15       I	Recht Affareit, Waren Afhaneit, Amit Affareit amf Erham Aggenereit     Interferent States       Table 1 Frequency count of themes within each sentiment-based category       S. No.     Theme     Negative Tweets       2     Sarcosm     18       3     Sarcosm     15       4     Sarcosm     15       5     Precautions     13       6     Precautions     13       7     Sarcosm     16       8     Healthcare workers     13       9     Government and leakership     30     35       9     Gover	Rever Aftered, Hirade Aftered and Ethical Aggeneral     Interference       Table 1 Frequency count of themes within each sentiment-based category       S. No.     Theme       Rest Aftered and Ethical Aggeneral       Image: Source of themes within each sentiment-based category       S. No.     Theme       Rest Aftered and Ethical Aggeneral       Image: Source of the sentiment based category       Source of the sentiment based category       Image: Source of the sentime		
Reach Atterat, IP arawn Atterat, and Atterat and Tables Ageneration     Interferences       Table 1 Frequency count of themes within each sentiment-based category     S. No.     Negative Tweets     Positive Tweets       S. No.     Theme     Negative Tweets     Count     Count       I     Emotional distress     18       Sarcosm     15       Violence, theft and abuse     15       I     Emotional distress     18       Sarcosm     15       I ferreduction and theme workers     15       I ferreductions     15       I ferreductions     15       I ferreductions     13       I ferreductions     14       I ferreductions     13       I ferreductions     14       I ferreductions     14       I ferreductions     14       I ferreductions     15       I ferreductions     14       I ferreductions     15       I ferreductions     14       I ferreductions     15       I ferreductions     14       I fereductions     15       I	Resh Afarat, Havat Aharat and Tahan, Agenerad       Information Disection	Rever Affered, Herad, Anna Affered and Ethan, Aggeneral       Table 1     Frequency count of themes within each sentiment-based category       S. No.     Theme     Negative Tweets       Count     Count     Count       Image: Count of themes within each sentiment-based category     Second       S. No.     Theme     Negative Tweets       Count     Count     Count       Image: Count of themes within each sentiment-based category     Second       Image: Count of themes within each sentiment-based category     Count       Image: Count of themes within each sentiment-based category     Count       Image: Count of themes within each sentiment-based category     Count       Image: Count of themes within each sentiment-based category     Count       Image: Count of themes within each sentiment and base     15       Image: Count of themes within each sentiment and base     15       Image: Count of themes within each sentiment and kakeship     30       Image: Count of themes within each sentiment and kakeship     30       Image: Count of themes within each sentiment and kakeship     30       Image: Count of themes within each sentiment and kakeship     30       Image: Count of themes within each sentiment and kakeship     30       Image: Count of themes within each sentiment and kakeship     30       Image: Count of themes within each sentiment and kakeship		
Table 1 Frequency count of themes within each sentiment-based category         S. No.       Theme       Negative Tweets Count       Positive Tweets Count       Notified Count         2       Emotional distress       18         3       Violence, their and abuse       9         4       Powerty and hunger       7         5       Unemployment       8         6       Erection and stress       18         7       Freeditional distress       18         8       Powerty and hunger       7         5       Unemployment       8         6       Economic impact       30         7       Freediticarre in the stress       31         9       Government and leadership       30         9       Government and leadership       30         10       Aster damper       10         11       Poelhi, Delhi, India       10         12       Aster damper       5         13       The stress       5         14       Scalai Number 6, near SHREE RAM MANDIR, Majlis Parl         14       Scalai Number 6, near SHREE RAM MANDIR, Majlis Parl         15       Mathin 110033, India       5         16       In	Table 1 Frequency count of themes within each sentiment-based category         S. No.       Theme       Negrouve tweets       Positive Tweets       Neutral         2       Count	Table 1 Frequency count of themes within each sentiment-based category         S. No.       Theme       Registive Tweets       Positive Tweets       Neutral Tweets         2       Emotional distress       18       Count		Information Discovery and Delivery
S. No.     Theme     Negative Tweets     Positive Tweets     Neutral       2     Emotional distress     18       3     Emotional distress     18       3     Violence, theft and abuse     9       3     Violence, theft and abuse     9       3     Violence, theft and abuse     9       4     Powetty and hunger     7       5     Unemployment     8       6     Economic impact     30       7     Government and lesdership     30       9     Government and lesdership     5       9     Government and lesdership     5       9     Government and lesdership     5	S. No.     Theme     Negative Tweets     Positive Tweets     Neutral Court       1     Emotional distress     18       2     Sarcasm     18       3     Violence, theft and abuse     9       3     Violence, theft and abuse     9       5     Unemployment     8       6     Economic (mpart     8       7     Government and kadeschip     30       9     Government and kadeschip     30       9     Government and kadeschip     30       9     Covernment and kadeschip     30       10     22       11     12       12     Covernment and kadeschip     12       14     Covernment and kadeschip     12       15     Covernment and kadeschip     13       16     Covernment and kadeschip     16       110033, India     15     16       110033, India     5     2       10     Long 77.176964°     2       10     29/10/21 04:34 PM     2 <th>S. No.     Theme     Negative Iweets count     Positive Tweets count     Positive Tweets count     Neutral Tweets count       Image: Stream     18 Stream     10 Stream     10 Stream</th> <th></th> <th></th>	S. No.     Theme     Negative Iweets count     Positive Tweets count     Positive Tweets count     Neutral Tweets count       Image: Stream     18 Stream     10 Stream		
Count     Count     Count     Count       3     Screation     15       3     Screation     15       4     Fourth and abuse     15       5     Unemployment     8       6     Economic impact     5       7     Precuritions     7       8     Government and leadership     30       9     Government and leadership     30       9     Government and Readership     30       1     Screation     16       1     Healthcare workers     4       1     Screation     13       1     Screation     13       2     Fatter Lainword     13       3     Screation     13       1     Screation     14       1     Screation     15       1     Screation     15       1     Screation     15       1     Screation     15       1     Screation     16       <	Court     Court     Court     Court     Court       1     Surveyin     15       3     Surveyin     15       3     Violence, theft and abuse     15       9     Powerty and hunger     7       1     Demony Synthem     8       6     Economic Impart     8       7     Precautions     7       8     Healthcare workers     7       9     Government and leadership     30       33     Theithcarrow of the Boothin in the Boothi	Count     Count     Count     Count     Count     Count       1     Streams     15       3     Streams     15       4     Free streams     15       5     Unemployment     7       6     Economic Impart     5       7     Precaritions     7       8     Headthcare workers     4       9     Government and leadership     30       33     Government and leadership     30       4     Headthcare workers     4       5     Original Streams     33       6     Government and leadership     30       33     Government and leadership     30       34     Headthcare workers     4       35     Government and leadership     30       36     Government and leadership     30       37     Headthcare Streams     16       38     Headthcare Streams     17       40     Headthcare Streams     18       41     Headthcare Streams     18       42     Headthcare Streams     18       43     Headthcare Streams     18       44     Headthcare Streams     18       45     Headthcare Streams     18       46     Headthca		
2     Emotioned distress     18       3     Surcasm     18       3     Woldence, theft and abuse     9       3     Powrity and hunger     7       5     Unemployment     8       6     Economic impact     30       7     Government and leadership     30       9     Government and leadership     5       9     Government and leadership <td< th=""><th>1     Emotional distrass     18       3     Violence, theft and abuse     9       3     Violence, theft and abuse     9       4     Powerty and hunger     7       5     Unemployment     8       6     Economic (mpact     5       7     Precautions     4       8     30     35     3       9     Government and kadeship     30     35       9     Government and kadeship     30     35       10     Entratainment     12       11     Kare's Delhi, Delhi, India     12       12     Mathematical Stress     14       14     Mathematical Stress     15       15     Mathematical Stress     16       16     Fortratainment     12       17     Stress     16       18     Mathematical Stress     16       19     Government and kadeship     30       10     Stress     16       11     Mathematical Stress     16       12     Stress     17       14     Stress     18       15     Mathematical Stress     16       110033, India     17     16       12     Mathematical Stress     16</th><th>Image: Second second</th><th></th><th></th></td<>	1     Emotional distrass     18       3     Violence, theft and abuse     9       3     Violence, theft and abuse     9       4     Powerty and hunger     7       5     Unemployment     8       6     Economic (mpact     5       7     Precautions     4       8     30     35     3       9     Government and kadeship     30     35       9     Government and kadeship     30     35       10     Entratainment     12       11     Kare's Delhi, Delhi, India     12       12     Mathematical Stress     14       14     Mathematical Stress     15       15     Mathematical Stress     16       16     Fortratainment     12       17     Stress     16       18     Mathematical Stress     16       19     Government and kadeship     30       10     Stress     16       11     Mathematical Stress     16       12     Stress     17       14     Stress     18       15     Mathematical Stress     16       110033, India     17     16       12     Mathematical Stress     16	Image: Second		
3     Sarcasm     15       3     Violence, theft and abuse     15       4     Powerty and hunger     7       5     Unemployment     8       6     Economic impact     5       7     Healthcare workers     7       8     Government and Readership     30     35       9     Government and Readership     30	3       Sarcasm       15         3       Violence, theft and abuse       15         9       Powerty and hunger       7         16       Powerty and hunger       7         16       Powerty and hunger       7         17       Precautions       15         18       Precautions       13         19       Precautions       13         10       13       13         10       13       15         10       10       15         10       10       15         11       Powerty and hunger       13         12       Precautions       14         13       Precautions       15         14       Powerty and headership       10         15       Powerty and Poelhi, Delhi, India       15         16       Powerty and Poelhi, Delhi, India       15         16       Powerty and Poelhi, Doga Powerty and Poelhi, Powerty and	Sarcasm     15       Violence, theft and abuse     15       Powerty and hunger     7       Recarding the state of th		Count Count
3       Violence, theft and abuse       9         4       Powerty and hunger       9         5       Unemployment       8         6       Economic (mpact       8         7       Precautions       30         8       Government and leadership       30         9       Government and leadership       30         9       Fater (appender and leadership)       30	Violence, theft and abuse Powerty and hunger Formations Formati	Violence, theft and abuse Powerty and hunger Konomic impact Proceeding and hunger Commic and kadenship Commic and kadenship Co		
<ul> <li>Proverty and hunger</li> <li>Unemployment</li> <li>Economic impact</li> <li>Precautions</li> <li>Precautions</li> <li>Team and headership</li> <li>Government and headership</li> <li>Both and the analysis</li> <li>Fetter taimport</li> <li>Government and headership</li> <li>Both and the analysis</li> <li>Fetter taimport</li> <li>Government and headership</li> <li>Both and the analysis</li> <li>Fetter taimport</li> <li>Government and headership</li> <li>Both and the analysis</li> <li>Both analysis</li> &lt;</ul>	<ul> <li>Powerty and hunger</li> <li>Precautions</li> <li>Precautions<td><ul> <li>Powerty and hunger</li> <li>Unemployment</li> <li>Benomic kinpart</li> <li>Feronic kinp</li></ul></td><td></td><td></td></li></ul>	<ul> <li>Powerty and hunger</li> <li>Unemployment</li> <li>Benomic kinpart</li> <li>Feronic kinp</li></ul>		
5     Unemployment     8       6     Reconverting     8       7     Reconverting     30       9     31     33       9     33     33       9     33     33       9     33     33       9     33     33       9     30     35       9     30     35       9     30     35       9     10     10       10     10     10       10     10     10       10     10     10       10     10     10       11     10033, India     5       10     Lat 28.717933°     2       10     Long 77.176964°     2       10     10/21 04:34 PM	5     Unemployment     8       6     Fondanick (mpact     8       7     Precountions     1       8     9     30     35     3       9     10     30     35     3       10     10     15     3       10     10     15     3       10     10     15     15       10     10     15     15       10     10     15     15       10     10     15     15       10     10     15     15       10     10     15     15       10     10     15     15       10     10     10     15       11     10     10     15       12     10     10     15       13     10     10     15       14     10     10     15       15     10     10     10       16     10     10     10       17     10     10     10       18     10     10     10       19     10     10     10       10     10     10     10       10     10     10     1	5       Unemployment       8       3         6       Economic (impact Precourbons       3       3       3         7       Precourbons       4       3       3       30         8       Commit (impact)       30       35       30       30       33       30         9       Precourbons       7       30       33       30       33       30         9       Precourbons       7       10 <td></td> <td></td>		
<ul> <li>Frequenting impart</li> <li>Frequenting impart</li> <li>Frequenting impart</li> <li>Frequenting impart</li> <li>Frequenting impart</li> <li>Frequenting impart</li> <li>Government and leadership</li> <li>Government and leadership</li> <li>Formation impart</li> <li>Formation impart</li> <li>Government and leadership</li> <li>Formation impart</li> <li>Formation impa</li></ul>	Image: Second	Konstruct     5     3       Readthcare workers     7     3       Readthcare workers     30     35     30       Government and kadership     30     35     30       Kaar + Delhi, Delhi, India     10     10     10       Kaar + Delhi, Dogs, Gali Number 6, near SHREE RAM MNDIR, Majlis Park, more and 10     10     10       Kaar + Delhi, Dogs, Gali Number 6, near SHREE 2, 20     24     24       Kaar + Dogs, Gali Number 6, near 2, 20     24     24       Long 77.176964°     24     24       Long 29/10/21 04:34 PM     24		
7       Precutations       7         9       Government and leadership       30       35       30         9       Government and leadership       30       35       30         10       10       10       10       10         10       10       10       10       10         10       10       10       10       10         10       10       10       10       10         10       10       10       10       10       10         10       10       10       10       10       10       10         10	7       Presultans       7         8       7       7         9       Government and kadership       30       35       3         9       Government and kadership       30       35       3         9       Formulation workers       30       35       3         10       Istel and happon       22       1         10       Istel and happon       13       1         10       Istel and happon       10       15         10       Istel and happon       10       15         10       Istel and happon       10       10         11       Istel and happon       10       10         12       Istel and happon       10       10         13       Istel and happon       10       10         14       Istel and happon       10       10         15       Istel and happon       10       10         14       Istel and happon       10       10         15       Istel and Istel and happon       10       10         16       Istel and Istel and happon       10       10         16       Istel and Istel and happon       10       10       10 <td>7       Presentations       7         9       Government and kadership       30       35       30         9       Government and kadership       30       33       30         10       13       13       12       2         10       15       16       15       18         10       16       16       18       18         10       10       16       18       18         10       10       16       18       18         10       10       16       18       18         10       10       16       18       18         10       10       10       18       18         10       10       10       18       18         10       10       10       19       19         10       10       10       10       19       10         10       10       10       10       10       10       10         10       10       10       10       10       10       10       10         10       10       10       10       10       10       10       10       10<td></td><td></td></td>	7       Presentations       7         9       Government and kadership       30       35       30         9       Government and kadership       30       33       30         10       13       13       12       2         10       15       16       15       18         10       16       16       18       18         10       10       16       18       18         10       10       16       18       18         10       10       16       18       18         10       10       16       18       18         10       10       10       18       18         10       10       10       18       18         10       10       10       19       19         10       10       10       10       19       10         10       10       10       10       10       10       10         10       10       10       10       10       10       10       10         10       10       10       10       10       10       10       10       10 <td></td> <td></td>		
Image: Second	#       Heithicarte workerts       4       30       35       3         Government and keasthp       30       35       3       3         Ferritraingreen       31       33       33       3         Ferritraingreen       10       10       10       10       10         Ferritraingreen       668, eGali Number 6, near SHREE RAM MANDIR, Majlis Parl       10       <	Image: Statistic weak weak     4       Image: Statistic weak weak     30       Image: Statistic weak weak weak     30       Image: Statistic weak weak weak     30       Image: Statistic weak weak weak weak     30       Image: Statistic weak weak weak weak weak weak     30       Image: Statistic weak weak weak weak weak weak weak weak		3
9         Government and leadership         30         35         30           1         33         33         33         33           1         1         33         33         33           1         1         1         1         1           1         1         1         1         1           1         1         1         1         1           1         1         1         1         1           1         1         1         1         1           1         1         1         1         1           1         1         1         1         1           1         1         1         1         1           1         1         1         1         1           1         1         1         1         1           1         1         1         1         1           1         1         1         1         1           1         1         1         1         1           1         1         1         1         1           1         1         1	9     Government and kadership     30     35     3       10     13     15     16       11     15     16     16       12     15     16     16       13     16     16       14     16     16       15     16     16       16     16     16       17     10     16       18     10     16       19     10     16       19     10     16       19     10     16       19     10     16       19     10     16       10     10     16       10     10     16       10     10     16       10     10     16       10     10     16       10     10     16       10     10     16       10     10     16       10     10     16       10     10     16       10     10     16       10     10     16       10     10     16       10     10     16       10     10     16       10     10     16	9     Government and kade/ship     30     35     30       10     13     13     10     10     10       10     13     10     10     10     10       10     10     10     10     10     10       10     10     10     10     10     10       10     10     10     10     10     10       10     10     10     10     10     10       10     10     10     10     10     10       10     10     10     10     10     10       10     10     10     10     10     10       10     10     10     10     10     10       10     10     10     10     10     10       10     10     10     10     10     10       10     10     10     10     10     10       10     10     10     10     10     10       10     10     10     10     10     10       10     10     10     10     10     10       10     10     10     10     10       10     10     10		
Failed California         33           Acar & Delhi, Delhi, India         33           Acar & Delhi, Delhi, India         33           Acar & Delhi, Delhi, India         33           Acar & C68, Gali Number 6, near SHREE RAM MANDIR, Majlis Park         5           Acar & Lat 28.717933°         5           Gle         Long 77.176964°           Sentin 29/10/21 04:34 PM         5	Image: State Stat	Image: Constraint of the state of		
Note:         Note: <td< td=""><td>1387         <td< td=""><td>188         188</td></td<><td></td><td></td></td></td<>	1387         1387 <td< td=""><td>188         188</td></td<> <td></td> <td></td>	188         188		
C68, Gali Number 6, near SHREE RAM MANDIR, Majlis Parl Mg Swi 110033, India Lat 28.717933° Long 77.176964° sertim 29/10/21 04:34 PM	C68, Gali Number 6, near SHREE RAM MANDIR, Majlis Parl C68, Gali Number 6, near SHREE RAM MANDIR, Majlis Parl Magaine 110033, India India Lat 28.717933° Long 77.176964° sentin 29/10/21 04:34 PM	C68, Gali Number 6, near SHREE RAM MANDIR, Majlis Park 20 C Lat 28.717933° Lat 28.7176964° gle sertin 29/10/21 04:34 PM	n Enertainpent	
C68, Gali Number 6, near SHREE RAM MANDIR, Majlis Parl Mg Swi 110033, India Lat 28.717933° Long 77.176964° sertim 29/10/21 04:34 PM	C68, Gali Number 6, near SHREE RAM MANDIR, Majlis Parl C68, Gali Number 6, near SHREE RAM MANDIR, Majlis Parl Mag 20110033, India Tag 20110033, India Long 77.176964° Sector 29/10/21 04:34 PM	United as C68, Gali Number 6, near SHREE RAM MANDIR, Majlis Park, frag sor 110033, India           Image: Star 110033, India         5           Image: Star 110033, India		
C68, Gali Number 6, near SHREE RAM MANDIR, Majlis Parl Mg Swi 110033, India Lat 28.717933° Long 77.176964° sertim 29/10/21 04:34 PM	C68, Gali Number 6, near SHREE RAM MANDIR, Majlis Parl C68, Gali Number 6, near SHREE RAM MANDIR, Majlis Parl Magaine 110033, India India Lat 28.717933° Long 77.176964° sentin 29/10/21 04:34 PM	C68, Gali Number 6, near SHREE RAM MANDIR, Majlis Park 7 24 7 24 9 29 20 20 20 20 20 20 20 20 20 20 20 20 20	Delhi, Delhi, India	
Vitions       12	Utobis       10033, India       12         Image Sor 110033, India	Utbols       12       0       12       0       0         Wr       Lat 28.717933°       5       24         Long 77.176964°       24         sentin 29/10/21 04:34 PM       4		
Imp surf110033, India       5	Imp for 110033, India       5         Imp for 10033, India       5	Imp Sor 110033, India         5           Imp Sor 10033, Indin	h and safety	<del>Shree RAM MA</del> NDIR, Majlis Park
Constraint         Second State         Second State <td>O         Description         Secretary         Secr</td> <td>Constraint         With Minimum         Lat 28.717933°         5         24           Constraint         Long 77.176964°         24         24         24         24           Gle         Long 77.176964°         24         2</td> <td>C68, Gali Number 6, near</td> <td></td>	O         Description         Secretary         Secr	Constraint         With Minimum         Lat 28.717933°         5         24           Constraint         Long 77.176964°         24         24         24         24           Gle         Long 77.176964°         24         2	C68, Gali Number 6, near	
Constraint         Lat 28.717933°         2           Long 77.176964°	Composition         Composition <thcomposition< th=""> <thcomposition< th=""></thcomposition<></thcomposition<>	Composition         Composition <thcomposition< th=""> <thcomposition< th=""></thcomposition<></thcomposition<>	ation = C68;= Gali Number 6, near	
gle Sentim 29/10/21 04:34 PM	gle 29/10/21 04:34 PM	gle 29/10/21 04:34 PM	ution • C68, Gali Number 6, near utions ing som110033, India	
glesentim 29/10/21 04:34 PM	9 e sentin 29/10/21 04:34 PM	glesentin 29/10/21 04:34 PM	vite a C68, Gali Number 6, near ing son 110033, India	5 24
			ation C68; Gali Number 6, near ing son110033, India ur Lat 28.717933°	5 24
			etion a C68; Gali Number 6, near ing son110033, India ur Lat 28.717933°	5 24
			etics - C68; Gali Number 6, near ing son110033, India <sup>Wr</sup> Lat 28.717933° Long 77.176964°	5 24
			C68, Gali Number 6, near ing sonf110033, India <sup>Wr</sup> Lat 28.717933° Long 77.176964°	5 24.

Pic 6: Dr. Ritika malik briefing about the session and FDP



Pic 7: Dr. Ritika malik explaining NVIVO through social media tweets

# LIST OF PARTICIPANTS

S.NO	NAME	CONTACT NO.
1	Ritika Aggarwal	9999440092
2	Tanya Garg	8130588092
3	Mehak Mittal	9999070922
4	Parul Chachra	9810114828
5	Dr. Ankita Srivastava	7738300603
6	Dr. Anuradha Dave	9457065886
7	Mukta Goel	9891691838
8	Dr Bhawna Bajpai	9818676351
9	Harshita Singh	7799944155
10	Jagadeesh Varanasi	8106237963
11	Mrs. Amandeep kaur	9229426191
12	Dr. KAYNAT NASSER	9997115634
13	RAKESH CHAWLA	9873302122
14	Prachi Aggarwal	9650002955
15	Charu Sarin	9650531133
16	DR ANMOL ARORA	9810097591
17	Dr. Anubhav Tiwari	9870420738
18	MAYUR TANEJA	9971806488
19	Anita Mathew	9497514224
20	Kushal C Ingole	9769140510
21	Swati Rohatgi	9873425877
22	Tejna Khosla	9650882070
23	AVINASH RAJ KUMAR	9456079149
24	Dr karmadkar Prakash Hemraj	9422209295
25	Saumya Chaturvedi	8700065318
26	VANI ANANDGAL	9866722094
27	ALISHA KUMAR	9811059158
28	Kirtika	9050362377
29	Hemant Batra	9560610530
30	Swati Luthra	9582447266
31	Surendra Mahato	9851030329
32	VISHAL KHANNA	9810139432
33	asha sanath	9844714102
34	Dr. Supriya Pottal Ray	8806998000
35	Dr. Mahesh Chandra Joshi	8283878200
36	Lakshay Sharma	8920233015
37	Dr. Amit Kumar	9991033395
38	Kiran Gandhi	7027897885
39	Mrs. Vinita Jamdade	9049732000
40	Dr. Neetu Jain	9818633268