

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	Rs.600
	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 68th 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)

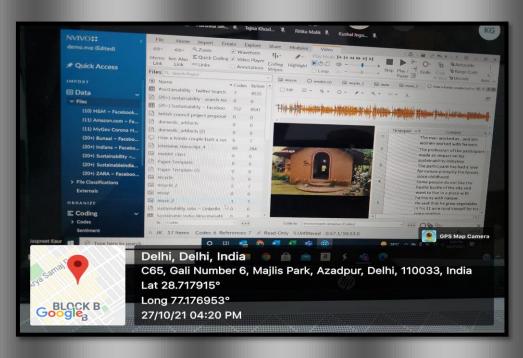
The FDP was started at 03:30 PM and first address was given by organiser Dr. Ritika Malik ,Assistant Professor, BVIMR, New Delhi .After giving brief introduction about Bharti Vidyapeeth and BVIMR, New Delhi . She then invited Dr Jaspreet kaur to take over the session. **Need line numbers? Save your source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



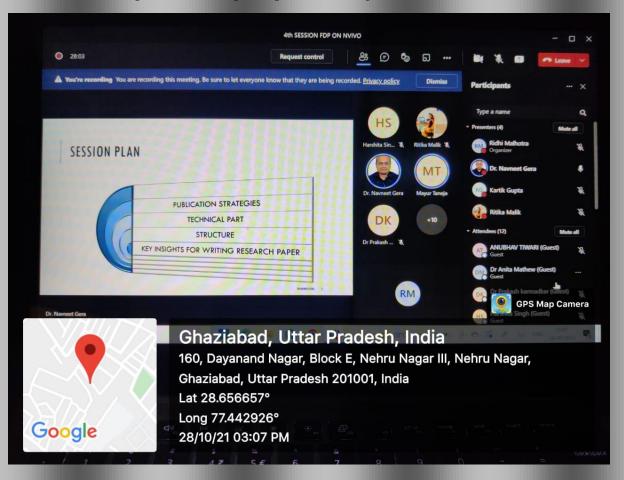


Day 4 (October 28,2021 i.e. Thursday)

The FDP was started at 3 pm and Dr. Navneet Gera started his session for 4th 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..





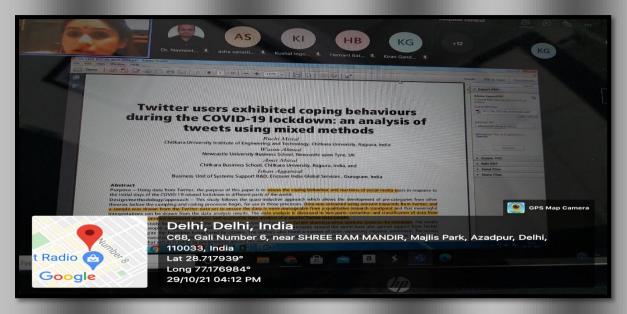
Pic 5: Group Picture of all participants attending the FDP.

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.

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



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

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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
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