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Original Research Article

Developing an instrument for assessing determinants of data use in evidence-based decision making: a principal component analysis at public primary health centres in Haryana, India

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ABSTRACT

Background: Evidence-based decision making (EBDM) by frontline health managers is the need of the hour in India and similar low- and middle-income countries (LMICs) for effective health policies and programs and factors affecting it needs to be ascertained. This study aims to develop an instrument for assessing determinants of data use for EBDM by frontline managers at public primary health centres.
Methods: We conducted a cross-sectional and analytical study using interview schedules capturing quantitative data from 120 medical officer in charges (MOICs) positioned at 120 primary health care units across 6 selected districts of Haryana, India. Principal component analysis (PCA) was used to generate clustered factors and reliability was tested.
Results: An instrument with three broad categories of determinants – organizational, technical, and individual (behaviour and technical) was generated. Within these, 154 variables were clustered into 27 factors. Each of the eight factors generated for organizational, technical, individual behaviour and three for individual technical determinants explained 60.5%, 59.8%, 57.7% and 68% of the total variance and had reliability of 0.75, 0.75, 0.78 and 0.80 respectively. Organizational, technical, and individual factors pertained to management meetings with superiors/subordinates, stakeholders influence, trainings in data sources, data quality and check mechanism, information adequacy, training seeking behaviour, involvement in multiple programs, incentivization, computer/software skills and knowledge.
Conclusions: The developed instrument comprised of generated factors which were rigorous, practicable, sorted, reliable and comprehensive, and effectively captured diverse determinants of data use for EBDM by frontline managers in peripheral health centres. The determinants resonate with the public health system scenario and has applicability in further analysis/settings.

Keywords: Data use, Determinants, Medical officer in charges, Evidence-based decision making, Principal component analysis

INTRODUCTION

Information holds high value in a health system by facilitating evidence-based decisions which culminate to strengthening of the health care delivery system and providing improved health services ultimately leading to the achievement of national and sub-national health objectives.[1] Evidence-based decisions are strongly linked to better health outcomes leading to effectively detecting problems, defining priorities, identifying innovative solutions, rational resource allocation, improved transparency, ensuring accountability, better health planning and efficient management of programs.[2] Hence, evidence-based decisions based on the harnessed information are the pressing need of the hour specially in low- and middle-income countries (LMICs).[3]

According to performance of routine information system management (PRISM) framework, factors govern health information systems performance and are determinants of data informed decisions. These comprise of 'technical factors' pertaining to quality of data, design, technologies, methodologies, procedures, tools, and instruments of the system; 'organizational factors' comprising of structure, roles, functions, and responsibilities, as well as the culture of information of key actors and users at each level of the health system and 'behavioural factors' which include knowledge, skills, attitudes, values, and motivation of the individuals that collect and use data. The concept of individual constraints was introduced in place of behavioural factors wherein both behaviour and skills of individuals to use information were separately considered. Hence, individual factors can be divided into two subgroups – 'individual behavioural' - "the behaviors of data users and how data are used for problem-solving and program improvement" and 'individual technical' - "knowledge, skills, attitudes, values, and motivation of the individuals that collect and use data".[4]

In India, primary health centres (PHCs), managed by frontline manager - a medical officer in charge (MOIC), form the foundational tier of public healthcare delivery in rural areas, providing essential primary care services at the grassroots level. Apart from the clinical duties, the administrative responsibilities of the MOIC of a PHC include supervision of staff, scrutinizing of programs, holding of monthly meetings to evaluate progress to deliberate upon steps for improvement, and capturing health information.[5] National guidelines emphasizes, "A PHC medical officer should ensure timely submission of updated monthly reports and records for program monitoring and strategic planning; utilize records to undertake population-based analytics, and planning of activities for the primary health care team".[6]

Hence, to promote evidence-based decision making at the grassroots level, it is imperative to consider various organizational, technical, and individual factors that determine data use. Specific technical, individual, and organizational activities can then be implemented to improve demand for, analysis, review, and use of routine health data in decision-making. An investigative tool was utilized in a previous study of three Indian states (Rajasthan, Maharashtra and Uttar Pradesh) which included numerous variables under each factor and hence was challenging for further use.[7] The factors should be elaborate, encompass all possible aspects and yet should be available in concise, comprehensive, and manageable form. The current study and analysis aims to formulate an instrument/tool with comprehensive factors to assess determinants of data use for evidence-based decisions at public primary health centres in Haryana, India. We applied a dimension-reduction technique - principal component analysis (PCA) to reduce the large set of variables to a concrete workable set of correlated determinants/factors that still contained most of the information of the large set. The analysis describes the reduction process and the components/factors generated thereafter.

METHODS

Design and setting

The cross-sectional and analytical study was conducted in six selected districts of Haryana, India based on maternal and child health indicators - full ante natal checkup rate and immunization rate.[8,9] Maximum variation/ heterogenous purposive sampling technique was used wherein MOICs at all peripheral primary PHCs in the district were selected. Only those medical officers were included in the study who were 'in charges', medical officers who were not 'in charges' at PHC level or were posted at any other facility were excluded. Data was collected from 120 MOICs at the facilities where they were posted by trained investigators through a pretested semi-structured interview schedule adapted from the PRISM framework and a previous study.[7] The interview schedule comprised of several elements under organizational, technical, and individual domain of determinants and each interview lasted for about 45-60 minutes. The data collection and analysis for the study were conducted over the period from December 2021 to May 2023.

Analysis

Initially organizational, technical, and individual factors were elaborate and comprised of numerous elements, therefore, to reduce and transform the large set of these independent variables into manageable, comprehensible components/factors, PCA was performed to extract components/factors with varimax orthogonal rotation. PCA has been defined as "a technique used to emphasize interpretability, commonly applied to systematically reduce the number of dimensions needed to describe datasets, but at the same time minimizing the loss of information".[10] Varimax rotation was used which generated factors/components uncorrelated to each other and facilitates the factors to better fit the data and has been defined as "varimax rotation is an orthogonal rotation method usually used for making the construct factors simple and explainable".[11] The data suitability was checked by testing assumptions. The sample size should be more than 100 and in the current study was 120, hence further assumptions were tested.[12] Sampling adequacy was checked by Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (>0.6) and factorability of the correlation matrix was assessed by Bartlett's test of sphericity (significance levels< 0.05).[13] The cut off value for factor loading was 0.5, scree plot was examined, and factors were generated for organizational, technical, individual behavioural and individual technical domain.[8] Since the data elements for individual technical factor were less, only three factors were generated. All the components generated had eigen values of more than one and the components/factors generated were named based on the interpretation of the variables/data elements they comprised of. The factor scores were generated by using regression method for maximum validity. Lastly, all the factors generated were tested for internal consistency by generating the reliability factor (Cronbach's alpha). All analyses, including PCA and reliability testing, were performed using statistical package for the social sciences (SPSS) version 22.0.

RESULTS

Descriptive characteristics

The sample comprised of 120 MOICs positioned at the PHC level in 6 districts and 28 blocks. Most respondents (75%) were based in rural facilities, while the rest (25%) were stationed in urban facilities. Most MOICs (80%) were doctors in medicine, with the remainder being dental surgeons. Only 18 respondents (15%) had pursued higher qualifications or postgraduate degrees. The average work experience at the current position of MOICs was 4.8 years and in the health system was 7.6 years.

Reliability and validity of the instrument

Kaiser-Meyer-Olkin measure of sampling adequacy for organizational, technical, individual behavioural and individual technical factors was greater than 0.6 indicating that the sample size was large enough to assess the factor structure and the items were compact and correlated. Bartlett's test of sphericity had significance levels less than 0.05 for all factors, indicating that the data were sufficient to proceed for the factor analysis and factors were generated. The reliability factor – Cronbach's alpha was greater than 0.7 for all factors as illustrated in Table 1.

Extraction of factors for the instrument

The final instrument comprised of three categories of determinants –organizational factors, technical factors, and individual factors. The 54, 45, 45, and 10 variables under organizational, technical, individual-behavioral, and individual-technical domains were reduced by using 0.5 as a cut-off value. The scree plot was examined, and eight organizational, eight technical, eight individual-behavioral, and three individual-technical factors, each having eigenvalues greater than one, were generated. The correlated factors were titled based on the comprehension of the consisting variables/data elements.

Organizational factors

For organizational factors, eight factors explained 60.5% of the total variance. The number of variables loading on to the factor, details of the variables and their loading value is explained in Table 2.

Technical factors

Eight technical factors were generated and accounted for 59.8% of the total variance. Table 3 explains the number of variables loading on to the factor, details of the variables and their loading value.

Individual factors

A total variance of 57.7% was explained by eight individual behavioural factors and 68% of variance was explained by three individual technical factors. The number of variables loading on to the factor, details of the variables and their loading value is explained in Table 4.

Table 1: Reliability and validity of the factors generated.

Factors	KMO test of sampling adequacy	Bartlett's test of sphericity-significance	Chi-square	Reliability factor-Cronbach's alpha
Organizational factor (OF)	0.677	0.000 (<0.05)	4755.713	0.749
Technical factor (TF)	0.661	0.000 (<0.05)	3256.001	0.753
Individual factor-behavioural (IF-B)	0.602	0.000 (<0.05)	3344.846	0.775
Individual factor-technical (IF-T)	0.667	0.000 (<0.05)	573.002	0.796

Table 2: Variables and factor loadings within organizational factor (OF).

Factors	Factor interpretation	Variables loading to the factor	Loading
Organizational factors			
Factor 1	External stakeholder influence (11 variables)	Civil society's influence in decision-making	0.872
		International donors' influence in decision-making	0.832
		Panchayat samitis' influence in decision-making	0.819
		Politicians' influence in decision-making	0.817
		Commercial sector's influence in decision-making	0.815
		Panchayat leaders' influence in decision-making	-0.813

Continued.

Factors	Factor interpretation	Variables loading to the factor	Loading
		Local politicians' influence in decision-making	0.812
		International NGOs' influence in decision-making	0.812
		Zila parishads' influence in decision-making	0.803
		Community groups' influence in decision-making	0.753
		Higher level administrators' influence in decision-making	0.669
Factor 2	Management meetings with superiors (6 variables)	Do you have management meetings with superiors	0.897
		Meetings involve review of performance in superiors' meetings	0.847
		Are data presented at superiors' meetings	0.784
		Are there follow up superiors' meetings	0.773
		When was last meeting with superiors	0.770
		Are there agreed set of indicators in superiors' meetings	0.615
Factor 3	Follow up mechanism after management meetings (8 variables)	Follow up reminder[5] are sent after superiors' meetings	0.728
		Follow up action taken for non-performance after subordinates' meeting	0.700
		Follow up supervisor visits after superiors' meetings	0.686
		Follow up submission of progress on time after superiors' meetings	0.666
		Follow up supervisor visits after subordinates' meeting	0.661
		Follow up reminder are sent after subordinates' meeting	0.652
		Follow up action taken for non-performance after superiors' meetings	0.652
		Follow up submission of progress on time after subordinates meeting	0.534
Factor 4	Management meetings with subordinates (6 variables)	Do you have management meetings with subordinates	0.876
		Meetings involve review of performance at subordinate meeting	0.866
		When was last meeting with subordinates	0.844
		Are there follow up subordinates' meetings	0.793
		Are there agreed set of indicators in subordinates' meetings	0.645
		Are data presented at subordinate' meetings	0.565
Factor 5	Data oriented and conducive organizational culture (9 variables)	Organizations/superiors are open to alternate views	0.714
		Organization/superiors emphasize data quality in regular reports	0.702
		Organization/superiors seek feedback from concerned persons	0.633
		Collected data reaches timely at relevant level	0.595
		Culture of looking at outcomes and outputs	0.580
		Facilities receive timely feedback on their submitted reports	0.549
		Organization/superiors explain what they expect from workers	0.538
		Analysis and feedback on data collected by superiors	0.512
		Organization/superiors allow disagreements before reaching a conclusion	0.503
Factor 6	Health management training received (3 variables)	Year mentioned of in-service health management training	0.967
		Any in-service training of health management	0.947
		Duration mentioned of in-service health management training	0.943
Factor 7	Influence of immediate external environment (3 variables)	Stakeholders influence on decision-making	0.825
		Political interference in decision-making	0.782
		Public pressure on decision-making	0.732
Factor 8	Suggestions for organizational strengthening (3 variables)	Suggestion-ensure that data needs are identified at all levels	0.734
		Suggestion-top leadership to use evidence-based decision-making	0.658
		Suggestion-improve timeliness of data	0.606

Table 3: Variables and factor loadings within technical factor (TF).

Factors	Factor interpretation	Variables loading to the factor	Loading
Technical factor			
Factor 1	Technical training received in data sources (7 variables)	Training received in surveys	0.812
		Training received in anemia tracking module (ATM)	0.811
		Training received in planning	0.795
		Training received in data analysis	0.779

Continued.

Factors	Factor interpretation	Variables loading to the factor	Loading
		Training received in data utilization	0.775
		Training received in maternal and infant death reporting system (MIDRS)	0.733
		Training received in health management information system (HMIS)	0.709
Factor 2	Perceived data quality (7 variables)	Rate quality in ATM	0.809
		Rate quality in MIDRS	0.807
		Rate quality in HMIS	0.78
		Rate quality in reproductive and child health (RCH) portal	0.746
		Rate quality in survey reports	0.698
		Data availability in graphs and charts	0.599
		Rate quality in published research	0.585
Factor 3	Data quality check mechanism (5 variables)	Are there systems to assure data quality in your work	0.891
		Are data checked for accuracy	0.858
		Are staff trained in data quality control	0.827
		Are manual reports compared with online entries	0.775
		Are HMIS/ATM/MIDRS data compared with survey reports	0.754
Factor 4	Suggestions for technical robustness (4 variables)	Suggestion-ensure data reports are available at all levels	0.855
		Suggestion-implement simple software at all levels	0.831
		Suggestion-further improve quality of data	0.827
		Suggestion-establish uniform data reporting/feedback mechanism	0.786
Factor 5	Technical training received in software packages (4 variables)	Any training in PowerPoint	0.85
		Any training in excel	0.819
		Any training in SPSS	0.785
		Any training in Epi Info	0.692
Factor 6	Availability of computer hardware (4 variables)	Do the computers in your unit belong to you	-0.697
		There is access to computer	0.697
		Computer speed is not slow	0.672
		No problem in power supply	-0.63
Factor 7	Information adequacy (3 variables)	Reasonable level of information without overload	0.758
		Certainty of real figures with no data duplication	0.724
		Data is of good quality	0.603
Factor 8	Established procedure for maintenance (2 variables)	Rate quality in ATM	0.836
		Rate quality in MIDRS	0.8

Table 4: Variables and factor loadings within individual factor.

Factors	Factor interpretation	Variables loading to the factor	Loading
Individual behavioural factor (IF-B)			
Factor 1	Involvement in multiple programs (5 variables)	Work in leprosy program	0.913
		Work in tuberculosis program	0.886
		Work in HIV/AIDS program	0.88
		Work in malaria program	0.869
		Work in blindness program	0.784
Factor 2	Training seeking behaviour (5 variables)	Training need on communication and presentation of data	0.891
		Training need on ensuring good quality data	0.871
		Training need on using data base software	0.838
		Training need on understanding HMIS data	0.76
		Training need on statistical analysis techniques	0.74
Factor 3	Training seeking behaviour for subordinate staff (5 variables)	Staff need training on ensuring good quality data	0.847
		Staff need training on communication and presentation of data	0.84
		Staff need training on using data base software	0.837
		Staff need training on understanding HMIS data	0.738
		Staff need training on statistical analysis techniques	0.638
Factor 4	NGO or private experience	Difference between public and NGO	0.837

Continued.

Factors	Factor interpretation	Variables loading to the factor	Loading
	(4 variables)	Do you work in NGO/private	0.826
		Difference between public and private	0.793
		No. of years in NGO/private	0.788
Factor 5	Performance evaluation mechanism (6 variables)	Performance is on work ethics/values	0.718
		Performance is as per pre-defined career advancement criteria	0.696
		Performance is evaluated on improvements in quality of care	0.688
		Collecting information is appreciated by co-workers and superiors	0.607
		Performance is evaluated on changes in service delivery indicators (rates)	0.607
		Staff are rewarded for good work	0.534
Factor 6	Training need on data management and use (2 variables)	Suggestion-training on use of data for program management	0.809
		Suggestion-training on importance of data collection, analysis and use to health providers	0.808
Factor 7	Existing incentivization	Recognition for performance on job	0.805
		Received verbal recognition from superiors	0.62
		Received certificate	0.579
Factor 8	Need/views on incenti-vization (recognition programs, cash rewards) (3 variables)	Views on cash rewards as incentives	0.795
		Views on employee recognition program as incentives	0.707
		Feelings about results-based financing	0.638
Individual technical factors (IF-T)			
Factor 1	Advanced analytical software knowledge (3 variables)	Do you or staff use STATA	0.934
		Do you or staff use Epi Info	0.889
		Do you or staff use SPSS	0.849
Factor 2	Basic computer skills (3 variables)	Computer use for data analysis	0.856
		Computer use for presentation for data	0.833
		Computer use for word processing	0.785
Factor 3	Basic software knowledge (2 variables)	Do you or staff use excel	0.905
		Do you or staff use PowerPoint	0.902

DISCUSSION

Main findings

The present study developed an instrument comprising of comprehensive, manageable, inclusive, and workable factors for each of the three organizational, technical, individual (behavioural and technical) determinants of health information systems performance and data use which can be used as a tool for future assessments. Through principal component analysis 154 correlated variables were clustered and transformed into a 27 uncorrelated variables/factors called 'principal components'. Our method was rigorous as we used 0.5 as the cut off value for factor loading and conducted visual inspection of scree plot suggesting of strong correlation within a factor and generation of relevant factors.[14,15] Reliability factor of 0.70 was assumed good as all domains had more than ten items and 88.9% factors had value of reliability factor more than 0.70.[16]

Comparison with previous studies

Our study introduces a novel instrument with elaborate, yet comprehensive factors designed to assess the determinants of data utilization in public health decision making. To our knowledge, this is the first research to generate these factors and develop such an instrument, filling a critical gap and providing a foundation for future studies to build upon in assessing and enhancing data-driven practices in public health.

Our instrument is robust not just because of the methods used for generating it but because of the inclusive and expansive variables which capture vital information and yet in a manageable form. The clustering of variables and the generated factors are relevant as they measure diverse and extensive dimensions of data use. Amongst organizational factors, essential factors like external stakeholder's influence captured the extent of influence of external stakeholders comprising of international, national and subnational stakeholders. This factor holds relevance as external stakeholder influence leads to collective decision making and designing of effective public health interventions.[17]

Organizational factor generated around management meetings whether with superiors, subordinates or follow up mechanisms include data-based review of performance and data presentation during meetings and serves as opportunity for staff at different level of hierarchies to congregate for common goals and programmatic actions. The factor exhibits applicability since previous studies emphasized the importance of a meeting platform for twoway communication, data use and sharing of information, dissemination of knowledge, discussion on ideas, evidence-based review of targets and performance, consensus on future plans and gap analysis.[18] Exploring data oriented and conducive culture incorporated organizational culture of looking at outputs and outcomes, feedback mechanism, timeliness of data, and perception of data quality as evidence suggests that a conducive and supportive environment is as an immutable enabler for evidence-based decision making.[4,19] Additionally, while decision making rests with the individual policy-makers, program managers, and other implementers, these individuals operate within the context of a system/organization with processes that directly impact the ability and extent to which evidence can be used as part of the decision making process.[20] Organizational processes for data use can be strengthened by leadership adopting and supporting evidence-based decisions and hence this factor also exhibits applicability and relevance.[21]

The technical factors generated in the instrument related to training and skill building for using routine health information systems, basic software and advanced analytical packages are pertinent since training received on the information systems adds to knowledge and abilities for accessing and utilizing data.[22] Our findings also emphasize measuring data quality as focusing on data quality is crucial, without which there is reluctance to use information for decision making.[23,24] Studies also reveal that if data quality is perceived to be satisfactory, it leads to increased data use for decision making and adds to further improvement in the quality of data, this creates a cycle of improved information, demand of data and information use eventually leading to improved health programs and policies.[25]

Technical robustness, availability of IT infrastructure and procedure for maintenance including ensuring the availability of reports at all levels, implementation of simple and comprehensible software at all levels, availability and access of computer hardware, establishment of uniform data reporting and feedback mechanism, troubleshooting and maintenance procedure are vital factors for functioning of information systems and data utilization for decisions.[4,26] Information adequacy as a factor needs to be explored to assess sufficiency of information and absence of data duplication. Duplicity of information has been described as a deterrent to data use by authors in Indian and global public health context.[22,27]

The individual factors encompassing both behavioural and technical factors were apt and relevant as it explored the individual aspect of data use for decisions. The health personnel using data are often involved in implementation of multiple health programs, dispensing their clinical and administrative services and thus have an expanded list of roles and responsibilities.[5] This calls for support of data for quick and efficient evidence-based decision making enabling simultaneous management of multiple programs and hence indicates towards the appropriateness of the engendered factor. Factors on training needs on ensuring good quality data, understanding routine data, using data base software, applying statistical analysis techniques and communication and presentation of data is an indication towards being motivated and positive towards capacity building for data understanding and utilization. In absence of such motivation for training, evidence-based programmatic decision making is less likely and routine data is not used for planning by grass root workers as has been asserted by authors in Indian context.[25,28,29]

Individual factors on performance evaluation and incentivization point towards a need for a structured system of incentives. This gives the much required boost to the sluggish momentum of motivation and accountability, furthermore leading to a transformative behaviour change with acceptance and enhancement of data use for programmatic decision making.[7] The factors generated on incentivization displays applicability since incentivization as an effective strategy for promoting data based decision making has been emphasized in previous studies.[7,22,29] Consequently, Ministry of Health and Family Welfare, Government of India has introduced incentivization in the form of performance based incentives (PBIs).[6] The individual technical factors on software knowledge and skills are vital as competency with analytic tasks and interpretation skills positively influence data use. It enables decision-makers to interpret and apply data, be able to distinguish which data they need to use and generate summaries of raw data.[22,30-32] This eventually will be very beneficial for the rural area PHCs and the population residing in nearby areas.[33]

Limitations

The study has few limitations. The sampling method was non-probability - purposive and the actual sample was 80% of the expected sample, hence this might have implications on generalizability of results. We were unable to test the instrument on a larger sample size and in diverse geographic contexts. To further validate the instrument, future studies should test it with more representative and larger samples and consider modifying items in each category of determinants.

CONCLUSION

Our study generated an instrument consisting of workable categories of organizational, technical, and individual determinants of data use with correlated variables which captures multifaceted information and yet was clustered into correlated and practicable factors. The comprehensive factors generated in the instrument aptly represent the information system utilization landscape of the public health care system in India and similar LMICs. Our study contributes to the limited research conducted in LMICs particularly on identification and extraction of such inclusive factors which can be used as a tool/instrument in future research in India and similar LMICs.

The generated factors were valid, reliable and exhibit applicability in further analysis, research and programmatic contexts. These can be used as a ready and simplified tool or adapted in similar settings across diverse geographies to assess performance of routine health information systems and factors affecting data utilization for evidence-based decision making. Using this instrument in different contexts can yield policy recommendations and program strategies to enhance evidence-based decision-making at the peripheral level, hence promoting a culture of evidence-based decision-making right at the grassroot level.

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