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Original article

Determinants of data use for programmatic evidence-based decision making at peripheral public health care centres in Haryana, India

Rupinder Sahota [a], Arindam Das [b,*], Fahad Afzal [b,c]

[a] Department of Population Health, London School of Hygiene & Tropical Medicine, London, WC1E 7HT, United Kingdom
[b] Institute of Health Management Research, IIHMR University, Jaipur, India
[c] Jhpiego India Country Office, New Delhi, India

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ABSTRACT

Background: Health policies and programs in India are put into practice at the local level, where the frontline managers -Medical Officers in Charges (MOICs) use data for evidence-based decision-making (EBDM) and implementing these programs. However, there are various organizational, technical, and individual determinants that can impact data use. The study aims to recognize the determinants of data-driven decision-making at the grassroots level.
Methods: The cross-sectional study collected primary empirical data from 120 MOICs from six identified districts in Haryana, India**.** Data utilization was the variable of interest and was measured through Data Utilization Score (DUS). Determinants affecting DUS were extracted through Principal Component Analysis (PCA). Hierarchical multiple regression analysis was used to identify predictors of data utilization from the extracted factors.
Results: MOICs used routine data to plan, implement, manage, and monitor health programs, and administrative activities. Actual skill for data usage (65 %) was less than the anticipated skill (82 %). Twenty-seven reliable organizational, technical, and individual factors were generated from the 154 variables explaining 57.7 %–68 % of the total variance. Regression analysis showed that management meetings with superiors/subordinates, data-conducive and promotive culture, perceived data quality, incentivization, basic software knowledge/skills, and training needs were among the most significant predictors of data usage.
Conclusion: Although a disparity exists between the expected and actual data utilization skills of MOICs, still data-based decisions can be enhanced by effective management meetings, fostering a robust data culture, prioritizing skill development, and incentivizing data use.

1. Introduction

Health systems strengthening through evidence-based decision-making (EBDM) is the need of the hour especially in Low- and Middle-Income Countries (LMICs) as they are grappling with the sustenance of resources, improvement of population health, and achievement of health goals and objectives. EBDM has been detailed as the process of distilling and disseminating the best available evidence from research, context, and experience and using that evidence to inform and improve public health practice and policy.[1] Evidence-based decisions are strongly linked to better health outcomes and lead to better health planning and efficient management of programs.[2]

Health information, one of the six building blocks of the health systems framework is the foundation of EBDM and has been described as a 'national asset'.[3] Although information holds high value in a health system, yet data-driven decision-making and the use of information systems are far from reality in many LMICs.[4] In India and other LMICs, humungous amount of data is passed on from the grassroots to a higher level or sits on the shelf without being used for programmatic decision-making, leading to a state of being 'data rich but information poor'.[5] While decision-making rests with the policymakers, program managers, and other implementers, the potential to attain health goals largely depends on the grassroots level where program level operational decision-making is done.[6] Data-driven decision-making is most relevant for the administrators positioned at the peripheral units of the health system. At these units, the data is generated and contextual factors with community needs are also kept into account while making decisions.[7]

Three types of factors act as determinants of data utilization

* Corresponding author. Institute of Health Management Research, IIHMR University, Prabhu Dayal Marg, Sanganer, Jaipur, Rajasthan, India.
E-mail address: arindam@iihmr.edu.in (A. Das).

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Organizational, Behavioral, and Technical as depicted in Fig. 1.[8] Researchers have analyzed individual factors that separately consider the behavior and skills of individuals to use information, these are '*Individual Behavioral' and* '*Individual Technical*'. Researchers have proposed a model to depict these factors and challenges, such as SBEA (Staging and Barriers in Electronic medical record Adoption) model.[9] With the knowledge of these determinants, specific technical, behavioral, and organizational activities can be implemented to improve demand for, analysis, review, and use of routine health data in decision-making.

In India, the government operated National Health Mission (NHM) has its focus on an evidence-based approach, promoting decentralization and local planning for effective resource utilization within the local context comprising of social, cultural, economic, and epidemiological landscape.[10] Primary Health Centres (PHCs) are the peripheral public health facilities at the rural/urban level, headed by a primary health care doctor called a 'Medical Officer in Charge (MOIC)'. The role of MOICs is very diverse, ranging from clinical functions, administrative responsibilities to capacity buidling.[11] The MOIC makes a plethora of decisions while dispensing these roles like supervision of staff, scrutinizing, and implementing of programs, holding monthly meetings to evaluate progress and deliberating on steps for improvement. For such decisions, it becomes essential to utilize the available routine information systems that have sufficient information and substantiate it with the understanding of community context and needs.[12,13]

This study aimed to identify and quantify the determinants of data use for evidence-based programmatic decision-making by MOICs posted at peripheral health units of Haryana, a north Indian state with 511 operational Primary Health Centres.[14] Despite the presence of a robust network of health information systems, there was limited use of data at the sub-district level.[15] Hence it became imperative to recognize the determinants of data-driven decision-making at the PHC.

2. Methods

2.1. Design and setting

A cross-sectional and analytical study design was adopted. Based on published literature, we selected six districts of Haryana on the premise of maternal and child health indicators.[16] The study period (data collection to analysis) was from December 2021 to May 2023.

A purposive sample comprised of 151 MOICs posted at the 151 peripheral health facilities - all rural PHCs and Urban Primary Health Centres (UPHCs) of the selected districts. Only those medical officers were included who were 'in charge' at the PHC, while those posted at the PHC level but not 'in charge' or posted at the district/state office were excluded. Data was collected by trained investigators from 120 MOICs at their respective facilities through a pretested interview schedule broadly based on the PRISM (Performance of Routine Information System Management) tool and adapted from a previous study.[17] The semi-structured interview schedule captured elements of data utilization, organizational, technical, and individual factors along with characteristics of respondents and each interview lasted for about 45–60 min. Variation between the actual and anticipated sample was due to vacancy of position or absenteeism in two subsequent visits.

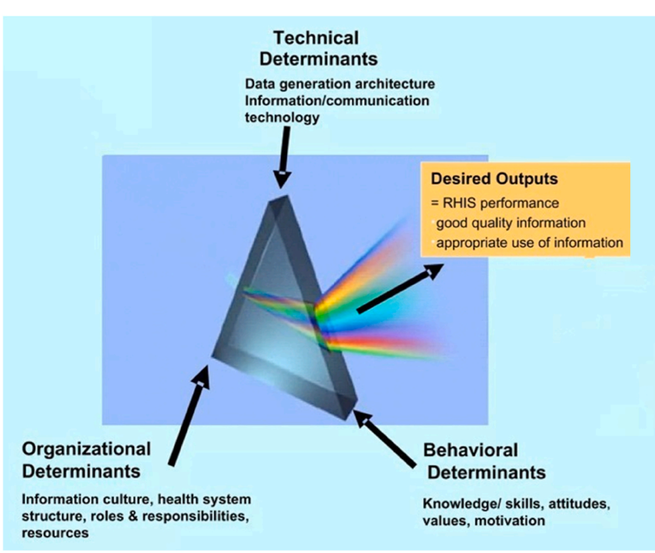

Fig. 1. Determinants of data use- Organizational, Technical, and Behavioral adapted PRISM framework for improving health information systems.

2.2. Analysis

Data analysis was divided into four steps:

Step 1- Mangement and segregation of data: Data was scrutinized and validated for enhancing its quality, accuracy, and completeness. Coding of open-ended questions and recoding of some data elements for normalization and positive polarity of data was done. Statistical Package for Social Sciences (SPSS-version 22) was used for the analysis of data. Segregation of the data variables/elements to be utilized for the formation of dependent and independent variables was done within Microsoft-Excel formats describing each variable/element along with their scoring criteria and description of the characteristics of respondents.

Step 2- Construction of Data Utilization Score (DUS)- Dependent Variable (DV): To assess the extent of data utilization for EBDM by MOICs at the peripheral level; a Data Utilization Score (DUS) - dependent variable was constructed which was a composite score comprising of subjective and objective dimensions. In subjective assessment, MOICs judged their own level of data use through a set of questions, while to assess the utilization status objectively and comprehensively, objective queries were administered, and facilities were observed for data use. Types of variables in the score were substitutable and variables/elements were normalized by converting them into unitless numbers having positive polarity. The aggregation approach was compensatory and simple; equal weights were rendered to pre-coded variables and reliability was tested.

Step 3- Factor reduction of Independent Variables (IVs) using Principal Component Analysis (PCA): Initially IVs- organizational, technical, and individual factors were elaborate with numerous elements, therefore, to reduce this large set into comprehensible components/factors, PCA was done to extract components/factors with varimax orthogonal rotation after testing assumptions.

Organizational, Technical, Individual Behavioral, and Individual Technical factors were independently extracted. The cut-off value for factor loading was kept at 0.5, a scree plot was examined and eight factors each were extracted for Organizational Factor (OF), Technical Factor (TF) and Individual Factor-Behavioral (IF–B) (Fig. 2).

Since data elements for Individual Factors-Technical (IF-T) were less, only three factors were extracted. The factors were reliable, having eigenvalues of more than one, and named according to the interpretation of the variables/data elements they comprised. Factor scores to be used in further regression analysis were generated by using the regression method for maximum validity.

Step 4- Determining predictors by hierarchical multiple linear regression and identification of barriers: The culminating step of data analysis established relationship between the DV and IVs. In our study, the IVs - extracted 'Organizational, Technical and Individual factors' were regressed upon the DV- 'Data Utilization Score.'

Hierarchical multiple linear regression was chosen to assess whether adding variables affected the model's predictive power significantly and to see the moderating effect of variables. IVs entered in the regression models were factor scores and were added

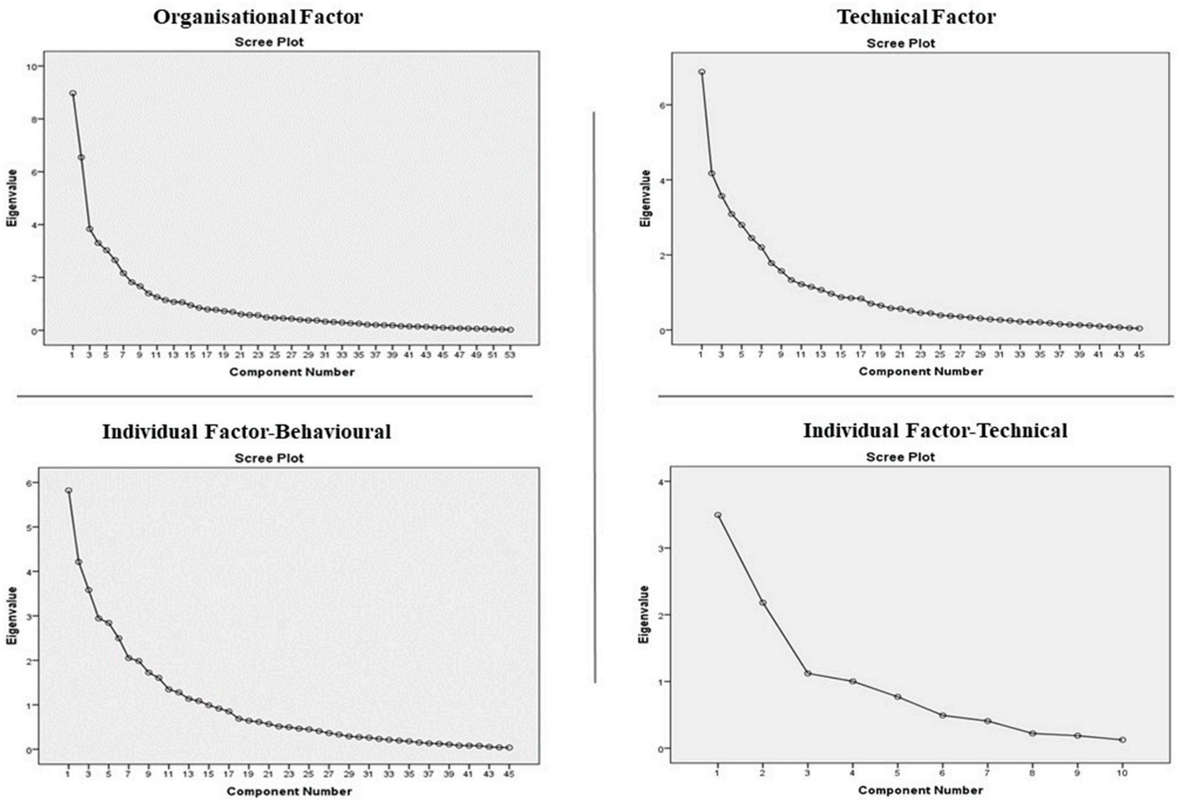

Fig. 2. Scree plots of organizational, technical, individual factor- behavioral and individual factor- technical.

in three blocks/models after testing assumptions.

In the first model, technical factors were regressed. The second model comprised of adding organizational factors in addition to already existing technical factors and in the third and final model, individual factors were added. Model summary for the three models was examined for Adjusted R^2, R^2, and R^2 Change, ANOVA (Analysis of Variance), F-values, and significance values. In the final model, unstandardized coefficients, standard error, and beta coefficients along with their level of significance were noted for each factor and factors were segregated according to their significance values ($p \leq 0.01$, $p \leq 0.05$, and $p \leq 0.1$) to generate the final model of predictors and dependent variable.

3. Results

3.1. Sample characteristics

Data analysis of 120 MOICs collectively revealed that the majority (80 %) of the surveyed MOICs were medical and 20 % were dental graduates with only 15 % having additional qualifications. Three-fourths of the MOICs were working at rural PHCs and the rest in urban PHCs. On average MOICs had 4.8 years of work experience in their current positions. and total experience of 7.6 years.

3.2. Generation of Data Utilization Score (DUS) - dependent variable (DV)

DUS was reliable (Cronbach's alpha 0.78) and normal as tested by statistics; skewness −0.176, standard error (SE) 0.22, kurtosis 0.581 (SE 0.44), Kolmogorov-Smirnov test 0.20 and Shapiro-Wilk test 0.49 and plots such as histogram with probability curve, normal QQ (Quantile-Quantile) Plot.

MOICs asserted involvement in decision-making, the presence of EBDM, and having the required skill to use data. Routine data was used for the management and monitoring of health programs, key objectives, indicators, and outputs along with medical supply/drug management (Table 1).

Routine data generated from health information systems was the most useful and was used to monitor maternal, and child health and family planning programs. Data was used during management meetings with subordinates and superiors and was used by staff for planning and monitoring targets. Skill test revealed that the actual skill for data usage (65 %) was less than the anticipated skills voiced by MOICs (82 %). There was limited knowledge of basic and program indicators, however,

Table 1
Data utilization description (n = 120).

Data Utilization Description	Count	Percentage
Subjective Dimensions		
Involvement in decision making	103	86
Decisions were based on evidence and facts	107	89
Equipped with skills to use data	98	82
Data used for-		
Monitoring key objectives, indicators and outputs	80	67
Medical supply/drug management	85	71
Formulating plans and reports	82	68
Budget management	76	64
Day to day program management	76	64
Management and monitoring health programs	97	81
Routine data useful than non-routine	87	73
Data used more for program support than record keeping	84	70
Data used during management meetings with superiors and subordinates	100	83
Data used by staff for planning and monitoring targets.	101	84
Objective Dimensions		
Actual skills to use data- correct answers in skill test	78	65
Recall of basic indicators of PHC area	49	41
Recall of program indicators of PHC area	22	18
Recall of indicators used in management meetings	67	56
Recent data displayed at facilities	75	63

more focus was on those indicators which were discussed and deliberated upon during monthly meetings. With respect to evident signs of data utilization, in two-thirds of the facilities up to date data was displayed as charts, tables, and graphs.

3.3. Extraction of organizational, technical, and individual factors -independent variables (IVs)

Our sample size of 120 met the assumption of having a sample size of 100 or more which was perquisite to conduct this analysis. Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy for Organizational, Technical, Individual Behavioral, and Individual Technical factors was 0.677, 0.661, 0.602, and 0.667 respectively indicating that the sample size was large enough to assess the factor structure (>0.6); factorability of the correlation matrix by Bartlett's test of sphericity revealed all factors to have the significance of 0.000 (<0.05) indicating that the data was sufficient to proceed for the factor analysis. Twenty-seven correlated and workable organizational, technical, and individual factors having eigenvalues of more than one were extracted from 154 elements, eight factors each for organizational, technical, and individual

Table 2
Factors generated through Principal Component Analysis (n = 120) with details of number of items loading to the factor, variance explained, reliability factor and eigenvalues.

Factor	Factor Interpretation	Initial Eigenvalues	Percentage of Variance	Reliability Factor (Cronbach's alpha)	Number of Loading Items
Organizational Factors (OF)					
Factor 1	External Stakeholder Influence	8.974	16.619	0.870	11
Factor 2	Management meetings with Superiors	6.606	12.234	0.865	7
Factor 3	Follow Up Mechanism after Management meetings	3.934	7.286	0.839	8
Factor 4	Management meetings with Subordinates	3.303	6.117	0.861	7
Factor 5	Data oriented and Conducive Organizational Culture	3.035	5.621	0.762	9
Factor 6	Health Management Training received	2.783	5.154	0.970	3
Factor 7	Influence of immediate external environment	2.205	4.083	0.831	3
Factor 8	Suggestions for organizational strengthening	1.824	3.378	0.537	3
Technical Factors (TF)					
Factor 1	Technical Training Received in Data Sources	6.878	15.285	0.895	7
Factor 2	Perceived Data Quality	4.172	9.271	0.872	7
Factor 3	Data Quality Check Mechanism	3.571	7.935	0.896	5
Factor 4	Suggestions for Technical Robustness	3.09	6.866	0.932	4
Factor 5	Technical Training Received in Software Packages	2.799	6.221	0.816	4
Factor 6	Availability of Computer Hardware	2.45	5.446	0.017	4
Factor 7	Information Adequacy	2.201	4.892	0.677	3
Factor 8	Established Procedure for Maintenance	1.782	3.96	0.776	2
Individual Factors-Behavioral (IF–B)					
Factor 1	Involvement in Multiple Programs	5.822	12.938	0.815	5
Factor 2	Training Seeking Behavior of Medical Officers	4.214	9.364	0.929	5
Factor 3	Training Seeking Behavior for Staff	3.583	7.963	0.894	5
Factor 4	NGO or Private Experience	2.942	6.539	0.844	4
Factor 5	Performance Evaluation Mechanism	2.844	6.319	0.899	6
Factor 6	Training need on data management and use	2.497	5.549	0.863	1
Factor 7	Existing Incentivization	2.052	4.559	0.934	3
Factor 8	Need/Views on Incentivization (Recognition programs, RBF, Cash Rewards)	1.986	4.413	0.717	3
Individual Factors-Technical (IF-T)					
Factor 1	Advanced Analytical Software Knowledge and Use	3.496	34.956	0.895	3
Factor 2	Basic Computer Skills	2.181	21.806	0.872	3
Factor 3	Basic Software Knowledge and Use	1.121	11.214	0.896	2

behavioral domains and three for individual technical factors. The interpreted factors and their details are presented in Table 2.

3.4. Identification of predictors by hierarchical multiple regression

Before performing hierarchical multiple regression, the assumptions of the same were tested. It was found that all such criteria were fulfilled. IVs were regressed upon the DV in 3 models-adding technical factors followed by organizational and individual factors. Model summary results are depicted in Table 3.

Hierarchical multiple regression models yielded a noteworthy R^2 Change, with a marked and highly significant rise from model one to model two and from model two to model three. ANOVA revealed the significance of all three models ($p \leq 0.05$, $p \leq 0.001$, and $p \leq 0.001$ respectively), *F* value was largest for the model with 27 predictors. The *F* values were the overall predictive effects which were different from the *F* for the amount of change experienced when adding an additional variable.

As per regression results, the third model, with 27 predictors evidently gave a better value for $R = 0.731$ suggesting a strong relationship between predictors and DV, with an R^2 of 0.534, thus 53.4 % of variance of DUS was accounted for. The change in R^2 was highly significant $F(11, 92) = 2.869$, $p < 0.01$, hence individual, technical, and organizational factors were predictors of DUS.

Out of the 27 factors, 11 factors comprising three organizational, two technical, four individual behavioral, and two individual technical were significant predictors of DUS (Table 4).

The final model equation was derived as: Y (Data Utilization Score) = β0 + β1(Perceived Data Quality) + β2 (Established maintenance procedure) + β3 (Management meeting with superiors) + β4 (Data oriented and Conducive Organizational Culture) + β5 (Management meeting with subordinates)+ β6 (Advanced Analytical Software Knowledge and Use) + β7 (Basic Software Knowledge and Use) + β8 (Involvement in multiple programs) + β9 (Training Seeking Behavior of Medical Officers) + β10 (Existing incentivization) + β11 (Need for incentivization).

Where, β0 = 55.254, β = 3.281, β2 = −1.947, β3 = 2.257, β4 = 3.886, β5 = 2.867, β6 = −1.885, β7 = 2.954, β8 = 2.552, β9 = 2.367, β10 = 2.903 and β11 = 2.019.

4. Discussion

The present study employed rigorous data analysis techniques to identify and quantify specific determinants of data use for evidence-based decision-making by MOICs at the grassroots level of the public health care delivery system in Haryana, India. This approach contrasts with previous studies that primarily evaluated, documented, and assessed the Routine Health Information System (RHIS) in India, with a limited focus on its impact on decision-making.[17,18]

The novelty of our study is the revelation of organizational factor - management meetings as a conspicuous and strong predictor of data use. Management meetings lead to collaborative working and a platform where deliberations take place between data users and producers, leading to the identification and addressing of key programmatic questions through analyses and interpretation of available data. It is a push towards data usage and evidence-based decision-making as data users interact with data producers and understand the availability and

Table 4
Models of hierarchical multiple regression analysis with significant factors.

Model No.	Factor category	Independent Variables	B	Std. Error	Beta
1	Technical factors	TF-Perceived data quality	3.112	1.162	0.23[a]
		TF-Data quality check mechanism	3.561	1.162	0.26[a]
2	Technical factors, Organizational factors	TF-Technical training received in data sources	2.198	1.115	0.16[c]
		TF-Perceived data quality	2.636	1.247	0.19[b]
		TF-Data quality check mechanism	2.227	1.146	0.16[c]
		OF-Management meetings with superiors	2.926	1.082	0.21[a]
		OF-Management meetings with subordinates	3.772	1.135	0.28[a]
		OF-Data oriented and conducive organizational culture	3.094	1.309	0.23[b]
		OF-Influence of immediate external environment	2.389	1.179	0.18[b]
3	Technical factors, Organizational factors, Individual factors	TF-Perceived data quality	3.281	1.264	0.24[b]
		TF-Established maintenance procedure	−1.947	1.150	−0.14[c]
		OF-Management meetings with superiors	2.257	1.052	0.17[b]
		OF-Management meetings with subordinates	3.886	1.116	0.29[a]
		OF-Data oriented and conducive organizational culture	2.867	1.458	0.21[c]
		IF-T-Advanced analytical software knowledge	−1.885	1.123	−0.14[c]
		IF-T-Basic software knowledge	2.954	1.179	0.22[b]
		IF-B-Involvement in multiple programs	2.552	1.219	0.19[b]
		IF-B-Training seeking behavior of medical officers	2.367	1.263	0.17[c]
		IF-B-Existing incentivization	2.903	1.159	0.22[b]
		IF-B-Need for incentivization	2.019	1.207	0.15[c]

[a] p=<0.01.
[b] p=<0.05.
[c] p=<0.1.

Table 3
Model Summary of hierarchical multiple regression analysis.

Model	R	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
1	0.398	0.098	12.67904	0.159	2.616	8	111	0.012
2	0.612	0.277	11.35015	0.216	4.439	8	103	0.000
3	0.731	0.397	10.36308	0.160	2.869	11	92	0.003

quality of data, methods of data collection, and barriers to data sharing.[19–21] Previous studies advocated strengthening of managerial function without which data use was not possible and declared it as a step before development of HMIS (Health Management Information System) for the primary health care level.[22] A need for sensitization of district heads to facilitate data-driven decision-making process and MOICs to train the field level workers on indicators/technical terms used in information systems was highlighted for which management meetings is an apt platform.

Within the context of technical factors, the most influential predictor was perceived data quality. Various authors have emphasized the importance of perceived data quality as a decisive factor in the utilization of data for decision-making.[23,24] Our study revealed the transition of perception of data quality from being poor to being good. In contrast, poor data quality in health information systems was stated as a challenge by many global researchers as well as Indian researchers.[25,26]

The lack of technical expertise of staff for generating summaries of raw data has been highlighted by the World Health Organization and different authors have laid emphasis on the cruciality of analytical and interpretation skills of users for data-driven decision-making.[27] Competency with analytic tasks appeared to positively influence data use, therefore the strongest predictor amongst individual-technical factors- 'basic software knowledge and use' identified in this study is highly relevant. The individual behavioral factor 'incentivization' influences data use for decision-making as it boosts motivation and accountability, leading to a behavior change with acceptance and enhancement of data use for programmatic decision-making. The deficient incentivization structure and the need for incentivization highlighted in our study reflect the findings of studies conducted previously.[28] Our study is suggestive of reinforcing such kind of incentivization at the grassroots level with inclusion of performance indicators linked to data use.

Another organizational predictor recognized by this study is data-oriented and conducive organizational culture which leads to value addition in technical and individual facets as well. Researchers have suggested a conducive and supportive environment comprising of timeliness, feedback mechanism, and communication about performance targets as an immutable enabler for evidence-based decision-making, without which efforts lead to sporadic, non-sustainable, and inconsistent attempts at data-driven decision-making.[26] An established feedback mechanism is a crucial aspect of enhancing EBDM. Our study findings are novel as they have revealed a supportive and data-oriented organizational culture which is contrary to the previous studies conducted in the Indian context.[29]

The individual behavioral factor -involvement in multiple programs is applicable as an MOIC is responsible for managing and implementing of Reproductive Child Health (RCH) mandate and national programs along with carrying out the administrative functions. Managing various programs simultaneously requires efficiency and time management skills for which support of data for quick and efficient decision making is taken.

Individual factor -training seeking behavior of decision makers at grassroots level points towards motivated and receptive behavior and impacts EBDM. Local capacity and skill building are crucial for information usage as it helps the decision makers to analyze the evidence and derive the best-fit strategy as an answer to emerging questions. Past studies have underscored that information systems hold no relevance without training of the grassroots functionaries.[30]

Studies wherein primary data has been collected from field-level functionaries for ascertaining determinants of data use for decision-making have been limited in India and other LMICs, hence, there is scope for undertaking such studies in similar contexts for better understanding of the determinants and level of data utilization. Our study adds to limited literature in India and highlights the various factors that act as influencers of data use.

5. Conclusion

To achieve health goals and ensure the success of national health programs, there is an urgent imperative for data-driven decision-making at the grassroots level of the public health system in India and other LMICs. Routine data from health information systems is used at the grassroot level for management of health programs, planning and monitoring of health targets and during management meetings. The determinants of data-driven decision-making in healthcare involve organizational, technical, and individual factors. Interdependent factors such as improved data quality perception, a culture promoting data use, lack of incentives, and skill gaps among decision-makers require holistic investigation by public health practitioners, academics, and policy-makers to promote evidence-based decisions in low- and middle-income countries.

Limitations

The sampling method was non-probability and the actual sample was 80 % of the expected sample, hence this might have implications on the generalizability of results. The current study established determinants of data use of decision-making and did not dwell into evidence-based decision-making leading to better health services and outcomes and therefore future research can explore this possibility.

Ethical compliance statement

The study did not involve any vulnerable subjects like pregnant women, children, differently abled, etc. Hence, it posed minimal risk to subjects. Necessary clearance and approval were obtained from the Institutional Review Board of IIHMR University, Jaipur, India (IRB approval no. IRB-FWA00018806).

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Author contribution statement

Rupinder Sahota and Arindam Das conceptualised and designed the study. Data collection and analysis was done by Rupinder Sahota. Rupinder Sahota took the lead in writing the paper and was supported by Fahad Afzal. Arindam Das gave critical inputs at different stages of the study. All authors read and approved the final version of the manuscript.

Conflicts of interest

The authors declare that they have no conflicts of interest.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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