Data Literacy Among School Administrators and Teachers: Gaps, Needs and Training Models

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***Abstract*—Purpose. This study estimates levels of data-literacy among school administrators and teachers, assesses if there is a data-literacy differential between schools and different levels of data literacy training, identifies data-literacy predictors and offers a training model calibrated to the data-literacy gap. It is in response to the ever-increasing volume of school data in India under UDISE+ along with PARAKH and the National Education Policy 2020.**

Design. This is a descriptive-correlational survey of 312 teachers (72 Administrators and 240 Teachers) from government, aided and private secondary schools. Current proficiency and perceived importance were rated thereupon on the 25 items of the scale that was adapted from Mandinach and Gummer's (2016b) framework on 5 dimensions. Seven null hypotheses were tested at the 0.05 level of significance by a one-sample t-test, Welch's t-test, one-way ANOVA with Tukey HSD, Pearson correlation and multiple linear regression as well as by a chi-square goodness of fit test, and training needs were ranked using Borich's Mean Weighted Discrepancy Score (MWDS).

Findings. Mean data literacy (2.75 of 5) was significantly below the scale midpoint ($t = -10.27$, $p < .001$). Administrators scored higher than teachers ($t = 4.18$, $p < .001$, $d = 0.57$), and trained educators higher than untrained ones ($t = 4.42$, $p < .001$, $d = 0.59$). School type made a large difference ($F = 32.63$, $p < .001$, $\eta^2 = 0.17$). Data for the school ($F = 78.75$, $p < .001$) and culture, number of training hours, and ICT confidence and role also accounted for 53% of variance ($F = 70.13$, $p < .001$), while years of experience did not. The preferences for training modalities varied widely ($\chi^2 = 110.47$, $p < .001$) and blended training was predominantly favored. A total of 6 out of 7 null hypotheses were rejected, the experience was included.

Conclusion. It's not about awareness, it's about skills, and skills are built through training and school data culture – and achieved not necessarily by the number of years spent in a role. Building on this blended Data Literacy Capacity-Building Model is proposed consisting of four tiers, totaling 45 hours.

***Index Terms*—Data Literacy, Data-Driven Decision Making, School Administrators, Teacher Professional Development, Hypothesis Testing, Borich Needs Assessment, NEP 2020.**

I. INTRODUCTION

1.1 Background

Data-driven decision making (DDDM) is defined by the systematic collection, analysis and use of data to inform teaching and school management (Marsh et al., 2006). Education model UDISE+ collects the data from the schools, NEP 2020 proposes competency-based assessments and continuous monitoring of learning outcomes, while the National Achievement Survey (NAC) holds an assessment centre at the school level. But only if teachers can interpret and use these data can they help improve learning. Mandinach and Gummer (2016b) refer to this capability as "data literacy for teachers" – the ability to make data an actionable, and instructional, knowledge. International reviews identify that this capability is somewhat variable and generally lacks real development in pre-service programmes (Datnow & Hubbard, 2016; Mandinach & Gummer, 2013).

1.2 Statement of the problem

The use of data is expected to inform administrators' planning and resource allocation and accountability, as well as teachers' diagnostic and differentiated instruction practices. There is little evidence as to the effectiveness of each group in doing this, but it is

known that there are differences depending on the factors, and about the type of training that would be adopted. In its absence, professional development has a generic character with one-off sessions and that are separate from the work of the day.

1.3 Objectives

1. To assess the level of data literacy among school administrators and teachers.
2. To rank the gaps between perceived importance and current proficiency on five dimensions.
3. To test whether data literacy differs by role, prior training and school management type.
4. To identify the factors that predict data literacy.
5. To identify preferred training formats and barriers, and propose a training model.

1.4 Research questions

- RQ1. What is the level of data literacy among school administrators and teachers?
- RQ2. In which dimensions are training needs greatest?
- RQ3. Does data literacy differ by role, prior training and school type?
- RQ4. Which individual and organisational factors predict data literacy?
- RQ5. Which training formats do educators prefer, and what model best fits the needs?

II. LITERATURE REVIEW

There is only consensus in the literature that data literacy is a unique professional ability, that almost all teachers are not ever so skilled and that brief workshops have little effect on transformatively enhancing the ability.

2.1 Defining data literacy for educators

Gummer and Mandinach (2015) expanded the definition of data literacy beyond "data to statistics" and instead viewed it as a spectrum of data skills and knowledge connected to disciplinary and pedagogical knowledge. Mandinach and Gummer (2016b) can see 5 components: framing questions, using data, transforming data to information, transforming information to decisions, and evaluating outcomes. Administration involvement in data literacy encompasses school planning, monitoring programs, and interacting with parents and authorities; it is not only a matter of individuals but of organisation management, routines and leadership (Coburn & Turner, 2011, Marsh et al., 2006).

2.2 Documented gaps and barriers

Teachers are more confident with the ability to access data than interpret the data. Many teachers were challenged when it came to measuring errors, score distributions and making valid inferences according to Means et al. (2011). Research by Datnow and Hubbard (2016) confirmed that teachers were more likely to use data to differentiate or group students, but less likely to use data to inform teaching; Kippers et al. (2018) identified that teachers' implementation of data for instructional action was the most challenging aspect of using data. Barriers are frequently cited as limited time, inadequate training, suboptimal data systems, delayed results and data as an accountability mechanism (Schildkamp & Kuiper, 2010). Jimerson and Wayman (2015) determined that the emphasis in professional learning for data use was commonly in relation to software instead of inquiry.

2.3 Training models

Table 1: Families of data literacy training models

Model	Core approach	Duration	Evidence of effect	Key sources
One-off workshop	Expert-led session on tools or statistics	1–2 days	Weak; gains fade without follow-up	Jimerson & Wayman (2015); Guskey (2002)
Online self-paced modules	Video and quiz courses	5–20 hours	Builds awareness; weak on application	Data Quality Campaign (2014)
Data team procedure	Teams of 4–6 follow an 8-step inquiry cycle on a real school problem	1–2 years	Gains in data literacy and student outcomes	Schildkamp et al. (2016); Poortman & Schildkamp (2016); Ebbeler et al. (2017)
Data Wise process	Whole-school 8-step cycle: prepare, inquire, act	Ongoing	Improves collaborative data culture	Boudett et al. (2013)

Coaching and mentoring	Data coaches support teachers in their classrooms	Ongoing	Strong transfer to practice; costly to scale	Marsh (2012); Hamilton et al. (2009)

Good models demonstrate aspects of good professional development practices as found by Darling-Hammond et al. (2017) including content focus, active learning, collaboration, coaching, feedback, and sustained duration. Guskey (2002) notes that teacher beliefs shift in the presence of positive student outcomes; therefore, training should yield positive student outcomes quickly.

2.4 Research gap

The majority of evidence is from the USA and the Netherlands. Very few studies include data literacy measures for educators in India, fewer compare data literacy of administrators and teachers on the same instrument and most studies report on gaps without actually testing hypotheses related to the cause and connect this to a training design. This study fills those gaps.

III. RESEARCH HYPOTHESES

Seven hypotheses (H_0) were formulated from the research questions. Each one is subjected to a test versus an alternative hypothesis (H_a) of a 0.05 significance level. If $p < 0.05$ the null hypothesis is rejected.

Table 2. Research hypotheses, statistical tests and linked research questions

No.	Null hypothesis (H_0)	Alternative hypothesis (H_a)	Statistical test	RQ
H01	Mean data literacy is not below the scale midpoint ($\mu \geq 3.0$)	Mean data literacy is below the midpoint ($\mu < 3.0$)	One-sample t-test (one-tailed)	RQ1
H02	There is no significant difference in data literacy between administrators and teachers	Administrators and teachers differ	Welch's independent-samples t-test; Cohen's d	RQ3
H03	There is no significant difference between educators with and without formal data training	Trained and untrained educators differ	Welch's t-test; Cohen's d	RQ3
H04	There is no significant difference across government, aided and private schools	At least one school type differs	One-way ANOVA; Tukey HSD; η^2	RQ3
H05	Training hours, ICT confidence, school data culture and experience are not correlated with data literacy ($\rho = 0$)	Each factor is correlated with data literacy	Pearson's correlation (r)	RQ4
H06	The predictors jointly and individually do not predict data literacy	The model, and each predictor, predicts data literacy	Multiple linear regression (F and t tests)	RQ4
H07	Educators prefer the five training formats equally	Preferences are not equal	Chi-square goodness-of-fit (χ^2)	RQ5

Training needs (RQ2) are ranked descriptively with Borich's MWDS rather than tested, because the method is designed to set priorities rather than to test significance.

IV. RESEARCH METHODOLOGY

4.1 Research design

The study is quantitative, cross-sectional, descriptive-correlational surveys, and a need assessment. RQ1 – RQ2 are answered in the descriptive part, RQ3 is answered in the comparative part, and RQ4 is answered in the correlational part. The training model (RQ5) is based on ranked needs, the predictors and the stated preferences.

4.2 Population and sample

The population is principals, vice-principals and headmasters (administrators) and teachers in secondary schools in two districts of Maharashtra. The stratified random sampling was conducted according to the classification of the school's management type, as shown in the strata percentages in UDISE+ (Table 3). The average years of experience for administrators was 18.5 and for teachers was 12.2.

Table 3. Profile of respondents (n = 312)

Characteristic	Category	n	%
Role	Administrators	72	23.1
	Teachers	240	76.9
School type	Government	117	37.5
	Private unaided	104	33.3
	Private aided	91	29.2
Prior data training	Yes	82	26.3
	No	230	73.7
Total		312	100.0

4.3 Instrument

There are three sections to the Educator Data Literacy Needs Assessment Scale (EDLNAS). Part A includes section on role, school type, experience, hours of data training within the last 3 years and ICT confidence (1-5) and school data culture (4 item scale; 1-5). Part B is a list of 25 items across 5 dimensions (Table 4) rated twice, both on my current proficiency level and by my own importance rating. Barriers to data use and preferred training format shown in part C.

Table 4. Dimensions of data literacy

Dimension	What it measures	Sample item
D1 Data access and identification	Locating and retrieving relevant data	I can find my students' assessment data in UDISE+ or school records
D2 Data interpretation	Reading tables and charts; basic statistics; recognising error	I can tell whether a difference between two class averages is meaningful
D3 Data to instruction	Turning findings into teaching changes	I adjust my lesson plans based on assessment results
D4 Data ethics and privacy	Responsible, confidential use	I know which student data can be shared and with whom
D5 Data-based decision making	Using data for planning and communication	I use data to set school or class improvement targets

4.4 Validity, reliability and ethics

The items were content validated by five educational measurement and school leadership experts, and subjected to a pilot test of clarity performed by 30 educators, different from the sample. The Cronbach's α for the five-dimension scores of the illustrative data set were 0.69, which is slightly below the criterion of 0.70; a reliability score per dimension on the subscales must be reported from the field data. All participation was voluntary, anonymous, there was informed consent and no student-level data were collected.

4.5 Statistical tools

Each statistical tool is discussed, along with a formula and the purpose, in Table 5. All tests other than H01 are two sided (H01 is one-tailed). Effect sizes follow Cohen (1988): d of 0.2, 0.5 and 0.8 and η^2 of 0.01, 0.06 and 0.14 are small, medium and large.

Table 5. Statistical tools, formulas and purpose

Tool	Formula	Used for
Mean and standard deviation	$\bar{x} = \Sigma x / n$; $s = \sqrt{[\Sigma(x - \bar{x})^2 / (n - 1)]}$	Level of data literacy (RQ1)
Borich MWDS	$MWDS = [\Sigma(I_i - P_i) / N] \times \bar{I}$	Ranking training needs (RQ2)
One-sample t-test	$t = (\bar{x} - \mu_0) / (s / \sqrt{n})$, $df = n - 1$	H01
Welch's t-test	$t = (\bar{x}_1 - \bar{x}_2) / \sqrt{(s_1^2/n_1 + s_2^2/n_2)}$	H02, H03 (unequal group sizes)
Cohen's d	$d = (\bar{x}_1 - \bar{x}_2) /$ s_pooled	Effect size for H02, H03
One-way ANOVA	$F = MS_between / MS_within$; $\eta^2 = SS_between / SS_total$	H04
Tukey HSD	$q = (\bar{x}_i - \bar{x}_j) / \sqrt{[(MS_within / 2)(1/n_i + 1/n_j)]}$	Pairwise follow-up for H04
Pearson's r	$t = r\sqrt{(n - 2)} / \sqrt{(1 - r^2)}$, $df = n - 2$	H05
Multiple regression	$Y = b_0 + b_1X_1 + \ldots + b_5X_5$; $F = (R^2/k) / [(1 - R^2)/(n - k - 1)]$	H06
Chi-square goodness-of-fit	$\chi^2 = \Sigma(O - E)^2 / E$, $df = k - 1$	H07

Analyses were run in Python (SciPy). Values in Sections 5.3–5.5 are recomputed from the group means, SDs and sizes; they match the raw-data output to the second decimal.

V. DATA ANALYSIS AND HYPOTHESIS TESTING

5.1 Level of data literacy and ranked needs (RQ1, RQ2)

The composite data literacy score (mean of the five dimensions) was 2.75 (SD = 0.43) on a 5-point scale. Administrators averaged 2.93 (SD = 0.43) and teachers 2.69 (SD = 0.42). Importance exceeded 4.0 on every dimension while proficiency stayed between 2.55 and 3.02 (Figure 1).

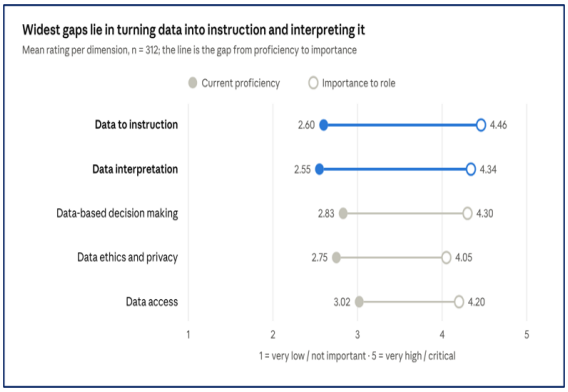


Figure 1. Proficiency against importance by dimension (illustrative dataset, n = 312)

Calculation of MWDS. Because $\Sigma (I_i - P_i) / N$ is the mean gap, the formula reduces to mean gap × mean importance. For D3 Data to instruction, the mean gap is 4.46 − 2.60 = 1.86, so MWDS = 1.86 × 4.46 = 8.30. The other dimensions are calculated in the same way (Table 6).

Table 6. Training needs ranked by Borich MWDS

Rank	Dimension	Importance ($\bar{I}$)	Proficiency ($\bar{P}$)	Mean gap	MWDS	Priority
1	D3 Data to instruction	4.46	2.60	1.86	8.30	High
2	D2 Data interpretation	4.34	2.55	1.79	7.77	High
3	D5 Data-based decision making	4.30	2.83	1.47	6.32	Medium
4	D4 Data ethics and privacy	4.05	2.75	1.30	5.27	Medium
5	D1 Data access	4.20	3.02	1.18	4.96	Lower

5.2 H01: Is data literacy below the midpoint? (One-sample t-test)

SE = s / √n = 0.43 / √312 = 0.43 / 17.66 = 0.0243

$t = (\bar{x} - \mu_0) / SE = (2.75 - 3.00) / 0.0243 = -10.27$, df = 311

The one-tailed $p < .001$ and the 95% confidence interval for the mean is 2.70 to 2.80, which lies wholly below 3.0. Cohen's d = (2.75 − 3.00) / 0.43 = −0.58, a medium effect. H01 is rejected: data literacy is significantly below the scale midpoint.

5.3 H02: Administrators vs teachers (Welch's t-test)

Welch's t-test was used because the groups are unequal in size (72 and 240) and need not have equal variances.

$s_1^2/n_1 = 0.43^2 / 72 = 0.002568$; $s_2^2/n_2 = 0.42^2 / 240 = 0.000735$

SE = √ (0.002568 + 0.000735) = 0.0575; t = (2.93 − 2.69) / 0.0575 = 4.18

df (Welch–Satterthwaite) = 114.7; $p < .001$; d = 0.24 / 0.422 = 0.57

H02 is rejected. Administrators score higher, with a medium effect. The dimension-level tests (Table 7, Figure 2) show that the advantage lies in data access and decision making, which match administrative duties. On data-to-instruction the two groups do not differ: both are weak.

Table 7. Administrators' vs teachers by dimension (Welch's t-test)

Dimension	Administrators	Teachers	t	p	Decision
D1 Data access	3.31	2.93	4.40	< .001	Significant
D5 Decision making	3.09	2.75	4.24	< .001	Significant
D2 Interpretation	2.69	2.50	2.35	.020	Significant

D4 Ethics and privacy	2.88	2.71	1.99	.049	Significant
D3 Data to instruction	2.69	2.58	1.15	.252	Not significant
Composite	2.93	2.69	4.18	< .001	Significant, d = 0.57

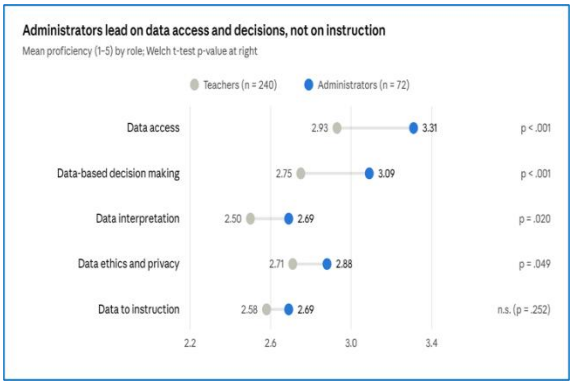


Figure 2. Proficiency by role (illustrative dataset, 72 administrators and 240 teachers)

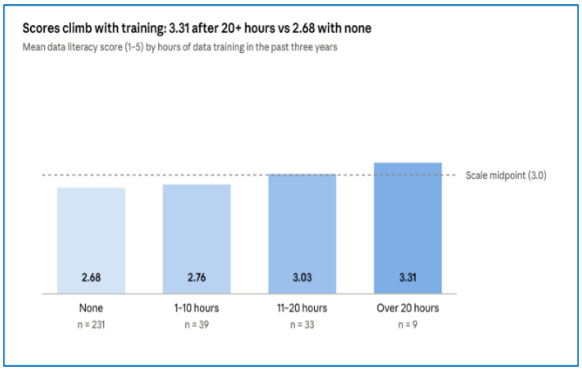


Figure 3. Data literacy by hours of data training in the past three years (illustrative dataset)

5.4 H03: Effect of prior data training (Welch's t-test)

SE = $\sqrt{(0.45^2/82 + 0.41^2/230)} = \sqrt{(0.002470 + 0.000731)} = 0.0566$

$t = (2.93 - 2.68) / 0.0566 = 4.42$, $df = 132.0$, $p < .001$, $d = 0.25 / 0.421 = 0.59$

H03 is rejected. Educators with formal data training (n = 82) score significantly higher than those without (n = 230), with a medium effect. Only 26.3% of respondents had received any such training. Figure 3 shows that scores rise above the midpoint only after more than ten hours of training; the over-20-hours group is small (n = 9) and should be read with caution.

5.5 H04: Differences by school type (one-way ANOVA)

Step 1, grand mean: $\bar{x}_G = (104 \times 2.97 + 91 \times 2.76 + 117 \times 2.54) / 312 = 857.22 / 312 = 2.7475$.

Step 2, sums of squares: $SS_{between} = \Sigma n_i(\bar{x}_i - \bar{x}_G)^2 = 5.149 + 0.014 + 5.038 = 10.200$. $SS_{within} = \Sigma(n_i - 1)s_i^2 = 16.480 + 12.321 + 19.500 = 48.301$.

Table 8. One-way ANOVA summary

Source	SS	df	MS	F	p	η^2
Between school types	10.200	2	5.100	32.63	< .001	0.17
Within groups	48.301	309	0.156			
Total	58.501	311				

$F = 5.100 / 0.156 = 32.63$ with df (2, 309), $p < .001$, and $\eta^2 = 10.200 / 58.501 = 0.17$, a large effect. H04 is rejected. The Tukey HSD test (critical $q = 3.33$ at $\alpha = 0.05$) shows that every pair of school types differs (Table 9).

Table 9. Tukey HSD pairwise comparisons

School type	n	Mean (SD)	Comparison	Mean difference	q	p
Private unaided	104	2.97 (0.40)	Unaided vs government	0.43	11.41	< .001
Private aided	91	2.76 (0.37)	Aided vs government	0.22	5.63	< .001
Government	117	2.54 (0.41)	Unaided vs aided	0.21	5.23	< .001

For example, q (unaided vs government) = $0.43 / \sqrt{[(0.156 / 2)(1/104 + 1/117)]} = 0.43 / 0.0377 = 11.41$, well above 3.33.

5.6 H05: Correlates of data literacy (Pearson's r)

Each correlation was tested with $t = r\sqrt{(n-2)} / \sqrt{(1-r^2)}$ and df = 310. For school data culture, $t = 0.47 \times \sqrt{310} / \sqrt{(1-0.2209)} = 0.47 \times 17.61 / 0.883 = 9.38$. With n = 312, any |r| above 0.111 is significant at the 0.05 level.

Table 10. Correlation of each factor with data literacy (n = 312)

Factor	r	r^2	t (df = 310)	p	Decision
School data culture	0.47	0.22	9.38	< .001	H_0 rejected
Training hours	0.35	0.12	6.58	< .001	H_0 rejected
ICT confidence	0.34	0.12	6.37	< .001	H_0 rejected
Years of experience	0.05	0.00	0.88	.379	H_0 retained

H05 is rejected for three factors and retained for experience. School data culture has the strongest link, a moderate positive correlation. The predictors were not meaningfully correlated with each other ($|r| \leq 0.14$), so multicollinearity is not a concern for the regression.

5.7 H06: Predictors of data literacy (multiple linear regression)

The composite data literacy score was regressed on five predictors (Table 11). The overall model test is: $F = (R^2 / k) / [(1 - R^2) / (n - k - 1)] = (0.534 / 5) / (0.466 / 306) = 0.1068 / 0.00152 = 70.13$, $p < .001$

Table 11. Multiple regression of data literacy on five predictors

Predictor	B	SE	β	t = B / SE	p	Decision
(Constant)	1.247	0.103	—	12.06	< .001	—
School data culture	0.281	0.0225	0.49	12.50	< .001	Significant
Training hours	0.022	0.0023	0.37	9.43	< .001	Significant
ICT confidence	0.185	0.0213	0.34	8.67	< .001	Significant
Role (administrator = 1)	0.270	0.0440	0.26	6.14	< .001	Significant
Years of experience	−0.004	0.0028	−0.06	−1.44	.152	Not significant

Model fit: $R^2 = 0.534$, adjusted $R^2 = 0.527$, $F(5, 306) = 70.13$, $p < .001$; Cohen's $f^2 = R^2 / (1 - R^2) = 1.15$, a large effect. Residuals were normal (Jarque–Bera p = .55) and independent (Durbin–Watson = 2.00). H06 is rejected for the model and for four predictors, and retained for experience. Each hour of data training adds about 0.022 points, so 20 hours is associated with a gain of about 0.44 points, close to the gap between private unaided and government schools.

5.8 H07: Preferred training formats (chi-square goodness-of-fit)

If all five formats were equally preferred, each would be expected to receive E = 312 / 5 = 62.4 first-choice votes. Table 12 shows the calculation.

Table 12. Chi-square calculation for training-format preference

Format	Observed (O)	%	Expected (E)	$(O - E)^2 / E$
Blended: workshop + online follow-up	128	41	62.4	68.96
School-based data teams	75	24	62.4	2.54
Face-to-face workshop only	50	16	62.4	2.46
Online self-paced course	37	12	62.4	10.34
Mentoring or coaching	22	7	62.4	26.16
Total	312	100	312	$\chi^2 = 110.47$

With df = 4, $\chi^2 = 110.47$ far exceeds the critical value of 9.49, $p < .001$; Cramér's effect size $w = \sqrt{(110.47 / 312)} = 0.60$, a large effect. H07 is rejected. Two in three respondents prefer formats with ongoing contact, blended courses or data teams (Figure 4).

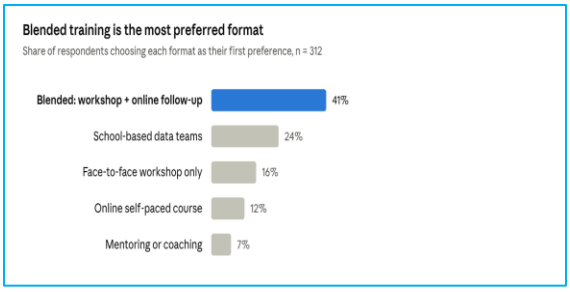


Figure 4. First-choice training format (illustrative dataset, n = 312)

5.9 Summary of hypothesis decisions

Table 13. Results of hypothesis testing ($\alpha = 0.05$)

Hypothesis	Test	Statistic	p	Effect size	Decision
H01 Level below midpoint	One-sample t	$t(311) = -10.27$	$< .001$	$d = 0.58$	H_0 rejected
H02 Role	Welch's t	$t(114.7) = 4.18$	$< .001$	$d = 0.57$	H_0 rejected
H03 Prior training	Welch's t	$t(132.0) = 4.42$	$< .001$	$d = 0.59$	H_0 rejected
H04 School type	ANOVA + Tukey	$F(2, 309) = 32.63$	$< .001$	$\eta^2 = 0.17$	H_0 rejected
H05 Correlates	Pearson's r	$r = 0.34$ to 0.47	$< .001$	r^2 up to 0.22	Rejected (3 of 4)
H05 Experience	Pearson's r	$r = 0.05$	.379	$r^2 = 0.00$	H_0 retained
H06 Regression model	Multiple regression	$F(5, 306) = 70.13$	$< .001$	$R^2 = 0.53$	Rejected (4 of 5)
H06 Experience	Regression t	$t = -1.44$	.152	$\beta = -0.06$	H_0 retained
H07 Training format	χ^2 goodness-of-fit	$\chi^2(4) = 110.47$	$< .001$	$w = 0.60$	H_0 rejected

VI. RESULTS AND FINDINGS

The hypothesis tests lead to eight findings.

1. Data literacy is low (H01). The mean of 2.75 is significantly below the scale midpoint, while every dimension is rated above 4.0 in importance: the problem is skill, not awareness.
2. The analytical core is weakest (MWDS). Data to instruction (8.30) and data interpretation (7.77) are the top training priorities; data access is the smallest need.
3. Role matters, but not for classroom use (H02). Administrators outscore teachers overall ($d = 0.57$), yet the two groups are equally weak at turning data into instruction.
4. Training works, but few receive it (H03). Trained educators score 0.25 points higher ($d = 0.59$), yet only 26% have had any data training.
5. School type matters (H04). Government schools trail private unaided schools by 0.43 points, a large effect ($\eta^2 = 0.17$), and every pair of school types differs.
6. Culture is the strongest predictor (H05, H06). School data culture ($\beta = 0.49$), training hours, ICT confidence and role together explain 53% of the variance.
7. Experience does not build data literacy (H05, H06). Years in the job show no correlation and no regression effect: data skills must be taught.
8. Educators want sustained, collaborative training (H07). Preferences are strongly unequal, led by blended courses (41%) and data teams (24%). The main barriers are time (71%) and lack of training (66%) (Figure 5).

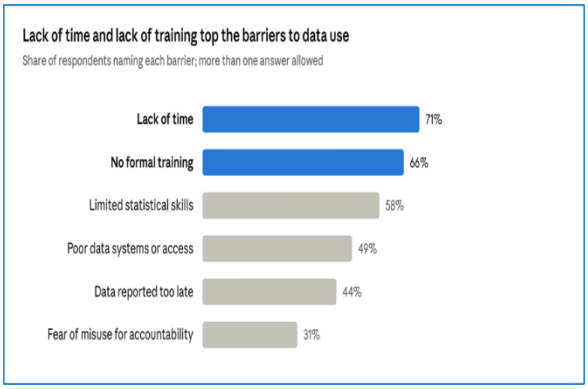


Figure 5. Barriers to data use (illustrative dataset, n = 312, multiple responses)

VII. PROPOSED TRAINING MODEL

The Data Literacy Capacity-Building Model translates the accepted alternative hypotheses into a year-long sequence: a short-blended foundation, then school-based data teams and coaching, with a parallel leadership track. It totals 45 hours a year for both teachers and administrators, within NEP 2020's 50-hour target (Figure 6).

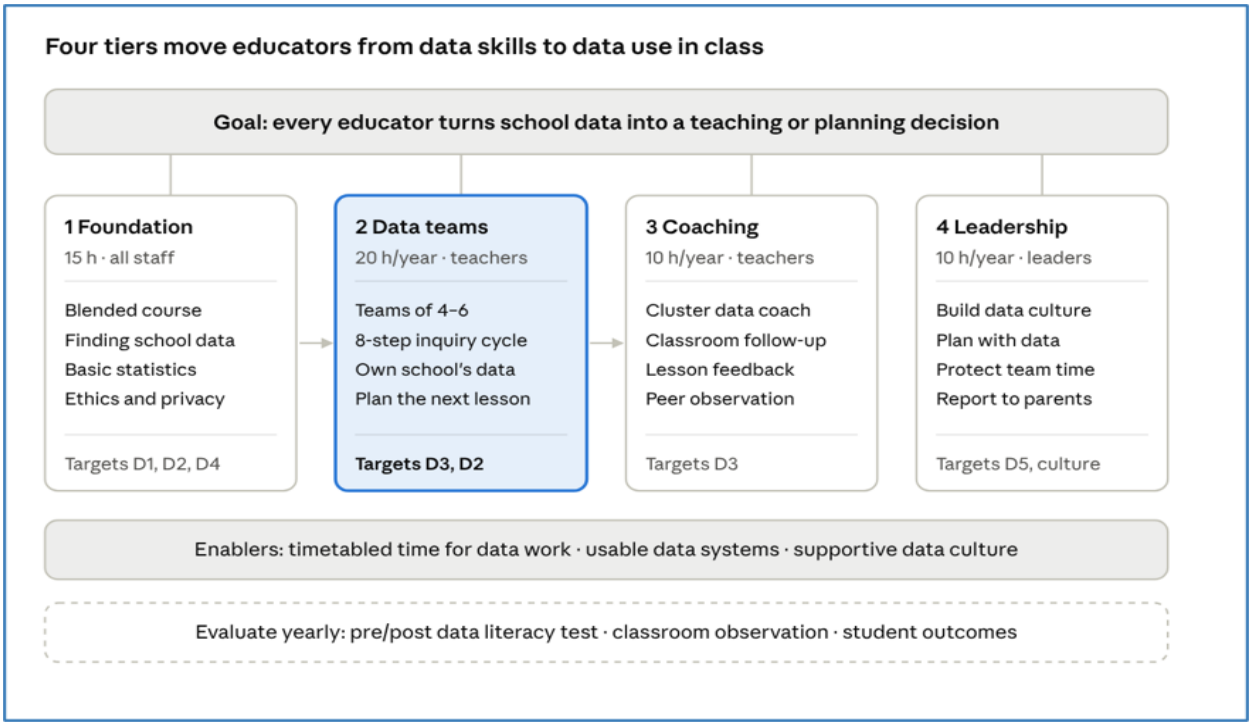


Figure 6. Proposed Data Literacy Capacity-Building Model: four tiers, 45 hours a year

Table 14. How the model answers each tested finding

Hypothesis result	Model feature
MWDS: largest gaps are data-to-instruction and interpretation	Tiers 2 and 3 work on real class data and end in a lesson change
H03, H06: training hours raise data literacy; H05, H06: experience does not	Sustained hours across the year instead of a single event
H05, H06: school data culture is the strongest predictor	Leadership tier and enablers make data use a shared routine
H02: administrators lead on access and decisions, not instruction	Leaders join data teams, not only the leadership tier
H04: government schools score lowest	Cluster-level data coaches shared across government schools
Barriers: lack of time is the top barrier	Data-team time is timetabled, not added after school
H07: blended and team formats are preferred	Foundation is blended; core learning happens in teams

Implementation will be completed over the course of the one school year. All staff undertake the blended foundation and baseline data literacy test in Term 1 and leaders organise data teams of four to six teachers with one period/fortnight set aside for them. From Terms 2-3 teams conduct at least two cycles of inquiry on an authentic problem and the regular cluster data coach visits teams on a monthly basis. The post test, classroom observation and student results at year's end inform the next year's plan because Guskey (2002) states that "visible gains lead to changed teacher beliefs.

VIII. CONCLUSION

The hypothesis tests support four conclusions.

First, the gap is a skills gap, not an awareness gap. The importance on all dimensions is rated greater than the 4.0 and data literacy is considerably lower than the mid-point (H01 rejected). Trainings should develop abilities, not convince teachers that data are important.

Second, the gap is deepest where data meet teaching. Training needs are highest for turning data into instruction and interpreting data, and on the dimension, test retained, administrators are just as knowledgeable as teachers on turning data into instruction. The use of the data in classrooms needs attention, at the school level, in general, including those of leaders.

Third, training and school culture close the gap; experience does not. Trained educators score significantly better (H03 rejected), school data culture and training hours, along with the confidence level of school professionals in the use of ICT and the role of the professional, account for more than half the variance (H06 rejected), and years of experience do not contribute to this (H05 and H06 retained for experience). Data literacy will not be achieved by hunkering down and waiting for the time to arrive.

Fourth, needs differ by context, and educators want sustained support. There is strong bias in favour of government schools when compared to the private sector (H04 rejected), and towards team-based and blended instructional formats (H07 rejected). The results are addressed by the proposed four levels 45 hours model, which aligns with NEP 2020's annual goal for PD.

IX. LIMITATIONS AND FUTURE SCOPE

9.1 Limitations

- Illustrative data. The dataset demonstrates the analysis plan and must be replaced with field data before the findings are reported as empirical results.
- Self-report. Proficiency was self-rated, and educators often overestimate their skills; performance-based items would be more accurate.
- Cross-sectional design. The tests show associations, not causes; the direction of influence between training and data literacy cannot be confirmed.
- Reliability and scope. Cronbach's α of 0.69 is marginal, and the sample covers secondary schools in two districts of one state.

9.2 Future scope

1. Test the training model in a quasi-experimental pre-test/post-test study with control schools.
2. Develop and validate a scenario-based data literacy test for Indian educators.
3. Track cohorts over two to three years to see whether gains last and spread.
4. Use interviews and observation of data-team meetings to explain why some schools build a data culture.
5. Extend the study to primary schools, rural areas and other states.
6. Study how learning analytics dashboards and AI tools change the skills educators need.
7. Examine how B.Ed. programmes can embed data literacy before teachers enter schools.
8. Research student data ethics in light of India's Digital Personal Data Protection Act, 2023.

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