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Strategy-User Profiles of Pre-Service Elementary Teachers: A Cluster-Analytic Study of Language Learning Strategies among D.El.Ed. Trainees in Tripura

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Abstract:

Variable-centred analyses of language learning strategies describe the average learner and can conceal meaningful subgroups. Adopting a person-centred approach, this study identified strategy-user profiles among 248 Diploma in Elementary Education (D.El.Ed.) trainees at District Institutes of Education and Training (DIETs) in Tripura, India, who completed Oxford's 50-item Strategy Inventory for Language Learning (SILL, Version 7.0; $\alpha = .96$). K-means cluster analysis of the six standardised SILL subscale scores yielded three profiles: high strategy users (n = 69, 27.8%; overall M = 4.37), moderate strategy users (n = 108, 43.5%; M = 3.56), and low strategy users (n = 71, 28.6%; M = 2.85). The profiles differed in elevation rather than shape: one-way ANOVAs were significant for every subscale ($\eta 2 = .55$ to .69), yet within each profile metacognitive strategies ranked highest and compensation strategies lowest, indicating a level-invariant internal asymmetry. Profile membership was significantly associated with year of study, $\chi 2(2) = 14.42$, $p < .001$, Cramér's V = .24: 41.2% of second-year trainees were high strategy users compared with 19.0% of first-year trainees. The association with gender was not significant ($p = .120$). The findings suggest that trainees differ chiefly in how much strategic behaviour they deploy, that this general propensity is greater in the senior cohort, and that nearly three in ten future elementary teachers are low strategy users. Implications are drawn for entry-point diagnosis and differentiated strategy-based instruction in teacher education under India's National Education Policy 2020.

Keywords: language learning strategies; SILL; cluster analysis; learner profiles; person-centred approach; pre-service teacher education; NEP 2020

1. Introduction

India's National Education Policy (NEP) 2020 and the National Curriculum Framework for School Education 2023 place communicative, activity-based language pedagogy at the centre of the foundational and preparatory stages (Government of India, 2020; NCERT, 2023). The realisation of that vision rests on elementary teachers, and therefore on the trainees currently preparing for that role. These trainees are themselves learners of English as a second language, and the strategies they use to learn it, being the behaviours they are most likely to model for children, are a matter of direct policy relevance. Understanding not merely the average strategic behaviour of this population but its internal variety is a precondition for designing teacher education that reaches every trainee.

Language learning strategies (LLS) are the specific actions and techniques learners employ to make learning faster, easier, more self-directed, and more transferable (Oxford, 1990). Since the "good language learner" studies (Rubin, 1975), strategic behaviour has been consistently associated with achievement and autonomy (Green & Oxford, 1995; Griffiths, 2013; O'Malley & Chamot, 1990). Oxford's (1990) Strategy Inventory for Language Learning (SILL) operationalises six categories: memory, cognitive, and compensation strategies, which engage the target language directly, and metacognitive, affective, and social strategies, which manage the learning process.

The teacher-education setting gives these constructs a distinctive weight. In ordinary learner populations, strategy research serves the individual: profiling a learner guides that learner's development. In a pre-service teacher population the stakes are multiplied, because each trainee's strategic repertoire will shortly be projected onto classrooms of children who take their teacher's habits as the model of what learning English involves. A teacher

education programme therefore needs to know not only the average strategic level of its intake but the distribution behind the average: how many trainees arrive strategically well equipped, how many arrive with little strategic behaviour at all, and whether the composition shifts as training proceeds. Questions of this kind are inherently person-centred; a mean cannot answer them.

Most SILL research is variable-centred: it asks how strategy categories behave across a sample, comparing means and correlating subscales with proficiency or demographic variables. Such analyses describe a hypothetical average learner and can obscure the fact that a sample is composed of unlike subgroups (Bergman & Magnusson, 1997). Person-centred methods, of which cluster analysis is the most accessible, instead ask what kinds of learners exist, grouping individuals whose whole strategy profiles resemble one another. The person-centred lens has yielded pedagogically consequential findings in LLS research. Kojic-Sabo and Lightbown (1999) distinguished eight approaches to vocabulary learning whose members differed sharply in success, with time and learner independence separating the more from the less effective profiles. Yamamori, Isoda, Hiromori, and Oxford (2003) combined strategy use, motivation, and achievement to identify distinct types of Japanese learners for whom identical strategy scores carried different functional meanings. Wong and Nunan (2011) likewise found patterned differences between more and less effective Hong Kong learners. Yet person-centred studies remain rare in the SILL literature, are almost absent in India, and have never, to the authors' knowledge, been applied to pre-service elementary teachers.

The present study addresses that gap with the same population examined in a companion variable-centred analysis of this dataset, in which trainees showed medium-to-high average strategy use with metacognitive strategies highest and compensation strategies lowest. Three research questions guided the analysis: (RQ1) How many distinct strategy-user profiles can be identified among D.El.Ed. trainees, and what characterises them? (RQ2) Do the profiles differ in shape, with different profiles favouring different strategy categories, or chiefly in elevation, that is, overall level of strategy use? (RQ3) Is profile membership associated with gender and year of study? Anticipating the results, a three-profile solution emerged; the profiles differed in elevation rather than shape; and membership was associated with year of study but not with gender.

2. Materials and Methods

2.1. Design and Participants

The study used a quantitative, cross-sectional survey design with a person-centred analytic strategy. Participants were 248 trainees of the two-year D.El.Ed. programme at DIETs in Tripura, India, recruited through institutional contact (convenience sampling), principally from DIET Kakraban and DIET Agartala and spanning the Gomati, South Tripura, West Tripura, Unakoti, and Sepahijala districts. The sample comprised 192 female (77.4%) and 56 male (22.6%) trainees; 102 (41.1%) had joined the programme in 2023, 142 (57.3%) in 2024, and 4 (1.6%) in 2025. Participation was voluntary and anonymous, and completion of the questionnaire constituted informed consent.

2.2. Instrument

Strategy use was measured with the SILL, Version 7.0 for learners of English (Oxford, 1990): 50 statements across six subscales (memory, items 1-9; cognitive, items 10-23; compensation, items 24-29; metacognitive, items 30-38; affective, items 39-44; social, items 45-50), each rated from 1 (never or almost never true of me) to 5 (always or almost always true of me). Reliability in this sample was high: Cronbach's $\alpha = .96$ overall, and .86, .89, .77, .89, .74, and .82 for the six subscales respectively.

2.3. Procedure and Data Screening

The questionnaire was administered online through Google Forms. All 248 returns were complete. Because the form permitted multiple selections on some items, 278 of 12,400 item responses (2.2%) contained more than one option; these were scored as the mean of the selected values. A sensitivity analysis discarding such responses left the descriptive structure of the data essentially unchanged.

2.4. Data Analysis

The six subscale means were standardised (z-scores) and submitted to k-means cluster analysis (Everitt, Landau, Leese, & Stahl, 2011) with 50 random initialisations. Candidate solutions of two to five clusters were compared using the within-cluster sum of squares (elbow criterion) and the average silhouette coefficient (Rousseeuw, 1987). The silhouette was highest for the two-cluster solution (.39) and next highest for three clusters (.30); the three-cluster solution was retained on joint criteria, as it preserved most of the reduction in within-cluster variance, produced three substantively interpretable and adequately sized groups rather than a bare high-low split, and mapped cleanly onto Oxford's (1990) usage bands. The stability of the retained solution was examined by re-clustering 100 bootstrap resamples and comparing the resulting assignments with the original ones; the mean adjusted Rand index was .75, indicating reasonable stability for survey data of this kind. Profile differences on each subscale were tested with one-way ANOVA and eta squared, and associations between profile membership and gender and year of study were tested with chi-square and Cramér's V, interpreted by Cohen's (1988) conventions. The four trainees admitted in 2025 were excluded from the cohort analysis. Analyses used Python 3.11 with scikit-learn 1.8 (Pedregosa et al., 2011), pandas, and SciPy; the code is available from the corresponding author on request. The study was not pre-registered.

3. Results

3.1. The Cluster Solution

The elbow criterion showed the largest drop in within-cluster variance in the move from two to three clusters, with clearly diminishing returns thereafter, and average silhouettes of .39, .30, .25, and .22 for the two- to five-cluster solutions. Balancing these indices against interpretability, the three-cluster solution was retained (Section 2.4). Bootstrap re-clustering supported its stability (mean adjusted Rand index = .75).

3.2. Three Strategy-User Profiles

Table 1 and Figure 1 present the profiles. High strategy users (n = 69, 27.8%) reported high use of every category (overall M = 4.37); moderate strategy users (n = 108, 43.5%), the largest group, sat near the sample means (overall M = 3.56); low strategy users (n = 71, 28.6%) fell in the medium band on every subscale (overall M = 2.85). One-way ANOVAs confirmed that the three profiles differed significantly on every subscale, with very large effects, $F(2, 245) = 147.3$ to 278.1, all $p < .001$, $\eta 2 = .55$ to .69, and on overall strategy use, $F(2, 245) = 560.4$, $p < .001$.

Table 1. Mean (SD) SILL subscale scores for the three strategy-user profiles (N = 248).

SILL subscale	High users (n = 69)	Moderate users (n = 108)	Low users (n = 71)	F(2, 245)	η2
Memory	4.25 (0.49)	3.42 (0.53)	2.79 (0.47)	147.7	.55
Cognitive	4.33 (0.41)	3.51 (0.35)	2.87 (0.35)	278.1	.69
Compensation	4.22 (0.54)	3.40 (0.48)	2.78 (0.49)	147.3	.55
Metacognitive	4.55 (0.37)	3.81 (0.37)	2.96 (0.50)	259.3	.68
Affective	4.36 (0.53)	3.47 (0.46)	2.90 (0.43)	165.5	.57
Social	4.49 (0.39)	3.74 (0.44)	2.80 (0.44)	276.5	.69
Overall	4.37	3.56	2.85	560.4	

Note. All F tests $p < .001$. η2 = eta squared.

The profiles differed in elevation, not in shape. The standardised cluster centroids were nearly uniform within each profile (approximately +1.1 on every subscale for high users, near 0 for moderate users, and about -1.0 for low users), and no profile favoured one category at the expense of another. Strikingly, the internal ordering of categories was identical in all three profiles: metacognitive strategies ranked first and compensation strategies last within the high, moderate, and low groups alike. The metacognitive-compensation asymmetry documented in the companion variable-centred analysis is therefore level-invariant: it characterises the strongest strategy users as much as the weakest.

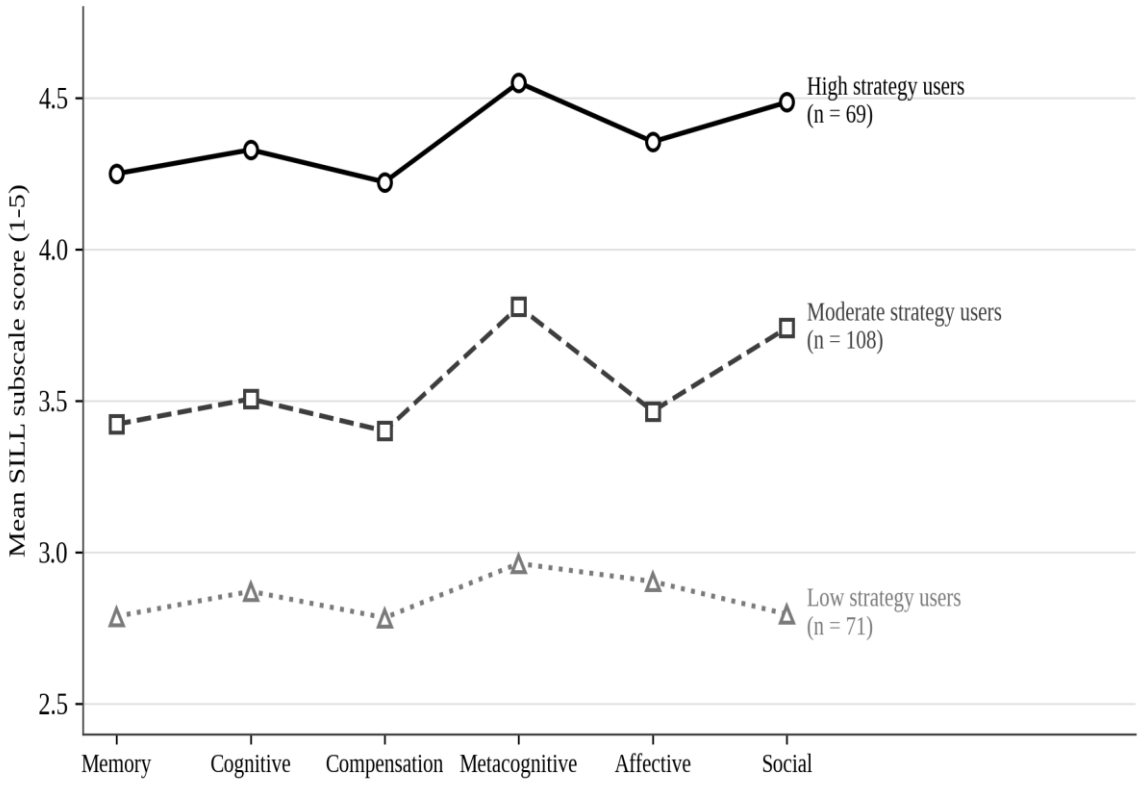

Figure 1. Mean SILL subscale scores for the three strategy-user profiles (N = 248). Within every profile, metacognitive strategies rank highest and compensation strategies lowest.

3.3. Profile Membership, Gender, and Year of Study

Profile membership was significantly associated with year of study (2023 versus 2024 entrants; n = 244), $\chi 2(2) = 14.42$, $p < .001$, Cramér's V = .24, a small-to-medium association. Among second-year trainees (2023 cohort), 41.2% were high strategy users, against 19.0% of first-year trainees (2024 cohort); conversely, half of the first-year cohort (50.0%) were moderate users and 31.0% low users, compared with 35.3% and 23.5% respectively among second-years. The association between profile membership and gender was not statistically significant, $\chi 2(2) = 4.23$, $p = .120$, Cramér's V = .13, although the descriptive pattern, with men constituting 31.0% of low users but only 17.4% of high users, ran in the direction reported in earlier strategy research and may merit examination in a larger male subsample.

4. Discussion

Three findings organise the discussion: D.El.Ed. trainees fall into three profiles distinguished by how much, not which kind of, strategic behaviour they report; the metacognitive-compensation asymmetry holds at every level of strategy use; and profile membership is associated with stage of training but not, statistically, with gender.

The elevation-based structure of the profiles is itself informative. Strategy use behaved in this sample as a general propensity: trainees who use many memory strategies also use many social and metacognitive ones, so clustering

recovered tiers rather than types. This coheres with the strong intercorrelations routinely observed among SILL subscales (Oxford, 2017) and with person-centred studies in which overall engagement, rather than a distinctive configuration, separated more from less successful learners (Kojic-Sabo & Lightbown, 1999). It contrasts instructively with Yamamori et al. (2003), who recovered shape-differentiated types when motivation and achievement entered the clustering alongside strategy use; the present data suggest that strategy frequency alone, in this population, varies mainly along a single dimension of strategic engagement. For teacher educators the practical meaning is that the first diagnostic question about a trainee is not "what kind of strategy user are you?" but "how much of a strategy user are you at all?".

That said, the profiles are not featureless. The internal ordering of categories, metacognitive first and compensation last, was identical in all three groups, replicating at every level the asymmetry identified in the companion variable-centred study and interpreted there as a residue of grammar-translation pedagogy. Its level-invariance sharpens the point: even the strongest strategy users, trainees whose overall engagement is exemplary, keep communicative repair strategies at the bottom of their repertoire. Strategy-based instruction that targeted only weak learners would therefore leave the compensation deficit of the strongest untouched; the deficit belongs to the pedagogical culture, not to a struggling subgroup.

The cohort finding carries the clearest developmental implication. Second-year trainees were more than twice as likely as first-years to be high strategy users, a small-to-medium association that is consistent with strategic growth across the two years of D.El.Ed. training, whether through the English methods coursework, accumulating classroom exposure, or general maturation within a professional programme. The cross-sectional design demands caution: cohort differences are not longitudinal change, and admission-year cohorts can differ for reasons unrelated to training, including selection and attrition. Still, the pattern is what a training effect would look like, and it offers teacher educators a testable and encouraging hypothesis rather than a mere description.

The gender result deserves an honest reading. Earlier strategy research frequently reported greater strategy use among women (Ehrman & Oxford, 1990; Green & Oxford, 1995); here the association between gender and profile membership did not reach significance, although the descriptive tilt, with men overrepresented among low users, pointed the conventional way. With only 56 men in a heavily female sample, power to detect a small association was limited, and the null should be treated as inconclusive rather than as evidence of no difference.

The moderate tier repays separate attention precisely because it is easy to overlook. Comprising 43.5% of the sample, it is the modal condition of the trainee population: neither strategically impoverished nor strategically fluent, sitting near the sample mean on every subscale. In variable-centred reporting this group simply is the average and attracts no comment; in the person-centred view it emerges as the largest single audience for strategy instruction, and the one for whom growth is most plausible, since its members already possess working versions of every strategy category. The cohort result suggests movement between tiers is possible within the span of training: if the second-year advantage among high users reflects development rather than selection, then the moderate tier is where that development is happening, and instruction that deliberately accelerates it, rather than concentrating exclusively on the weakest trainees, may offer the largest aggregate return.

The pedagogical implications follow the profile structure. Nearly three in ten future elementary teachers were low strategy users across the board, in the medium band on every subscale; these trainees are identifiable at programme entry with a freely available instrument, and they, with the moderate majority, define the realistic starting point for strategy-based instruction in DIETs. A differentiated approach suggests itself: foundational, explicitly modelled strategy instruction for the low tier; consolidation and expansion, particularly of the direct strategies, for the moderate tier; and, for the high tier, refinement aimed at the one weakness they share with everyone else, the compensation repertoire. Embedding such instruction in D.El.Ed. English courses aligns directly with the communicative ambitions of NEP 2020 and the National Curriculum Framework 2023 (Government of India, 2020; NCERT, 2023). The limitations of the study, namely its cross-sectional and self-report design, its single-state convenience sample, the determinism of k-means and the modest silhouette values typical of continuous survey data, and the unmeasured proficiency of participants, mark the boundaries of these claims. Future work should confirm the profile structure with model-based methods such as latent profile analysis, follow trainees

longitudinally to test the training-growth interpretation of the cohort difference, and link profile membership to observed classroom behaviour and measured proficiency.

5. Conclusions

Cluster analysis of 248 D.El.Ed. trainees' SILL responses yielded three strategy-user profiles, high (27.8%), moderate (43.5%), and low (28.6%), that differ in the amount rather than the kind of strategic behaviour deployed, that keep metacognitive strategies first and compensation strategies last at every level, and that are associated with stage of training but not detectably with gender. For elementary teacher education the message is twofold. First, strategic engagement is unevenly distributed and identifiable: a fifty-item questionnaire administered at entry can locate the roughly three in ten trainees who need foundational strategy instruction before they can be expected to model strategic language learning for children. Second, one weakness is universal: whatever their tier, trainees leave communicative repair strategies at the bottom of their repertoire, so compensation-focused instruction belongs in the common core of D.El.Ed. English preparation, not in its remedial margins. Both steps are inexpensive, and both serve the communicative classroom that NEP 2020 envisages.

Supplementary Materials

The anonymised dataset and the Python analysis code are available from the corresponding author on reasonable request.

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Author Contributions

Conceptualisation and methodology, N.M. and P.S.S.; data collection, formal analysis and writing, original draft preparation, N.M.; supervision, review and editing, P.S.S. Both authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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