One Source, Many Hands: Script Evolution, Writer Familiarity, and Cross-Script Influence in the Forensic Examination of Devanagari Handwriting

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Received 12, June 2026, Revised 15, July 2026, Accepted 14, August2026

Abstract
Forensic handwriting examination assumes that mature writing is both habitual and individual, but the discipline's standard protocols were built around the Latin script. Devanagari does not fit that model. Its letters hang from a headline, the shirorekha; vowels attach as matras occupying distinct vertical zones; consonant clusters fuse into conjuncts; and a few characters deliberately break the headline.

We tested whether a headline-anchored framework could capture these features quantitatively. Using Digimizer image-analysis software, we measured slant relative to the fitted headline, zonal proportions, headline continuity (HCI), matra placement, pen-lift frequency, and stroke width as a proxy for pen pressure in 350 contemporary writers, stratified by familiarity with Devanagari, frequency of use, signature script, and first script.

Familiar writers produced markedly more continuous headlines (HCI 0.91 vs. 0.64), steadier slant (SD 2.8° vs. 7.6°), and fewer pen lifts per word (0.8 vs. 3.4); all differences were significant at $p < 0.001$ with large effect sizes surviving Holm–Bonferroni correction. First-script background shaped the writing as well. Writers whose first script shares Brahmi-derived geometry and headline structure (Gujarati, Gurmukhi, Bengali) transferred Devanagari-consistent features, whereas Telugu-first writers showed native-script interference: exaggerated bowl curvature and fragmented headlines. A linear discriminant model using HCI, slant consistency, pen-lift frequency, and matra offset assigned writers to familiarity groups with 92.6% leave-one-out accuracy (95% CI 89.1–94.7%; sensitivity 94.0%, specificity 90.7%). This remains group-level attribution; it does not identify individual writers.

The results indicate that reliable Devanagari examination requires headline-anchored, script-specific protocols. The quantitative indices validated here provide a measurement basis that, after laboratory-level validation, could support examination and testimony under the Bharatiya Sakshya Adhiniyam, 2023.

Keywords: questioned documents; Devanagari; shirorekha; handwriting individuality; cross-script influence; Digimizer; forensic document examination

How to cite this article: Nitin Tyagi1 Prashant Agrawal2*. One Source, Many Hands: Script Evolution, Writer Familiarity, and Cross-Script Influence in the Forensic Examination of Devanagari Handwriting. Int J Drug Deliv Technol. 2026;16(77s):838-851. DOI: 10.25258/ijddt.16.77s.100.

1. Introduction

Forensic handwriting examination grows harder where scripts have multiplied, diverged, and simplified over centuries. The writing systems of South Asia all trace back to a single documented ancestor: the Brahmi script of the first millennium BCE [1,2]. Devanagari, Gujarati, Gurmukhi, Bengali–Assamese, Odia, Telugu, Kannada, Tamil, and Malayalam all descend from it [2,3]. Fig. 1 shows the main genealogical relationships that frame the cross-script comparisons in this study.

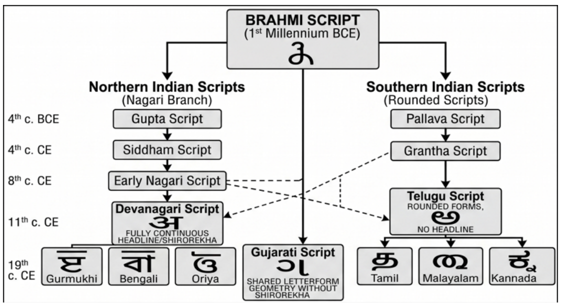

Fig. 1. Genealogy of major Brahmi-derived scripts, indicating headline treatment in the Nagari branch. Solid arrows denote direct descent; broken arrows denote documented cross-branch influence. The Nagari line consolidates the proto-headline into the continuous shirorekha of Devanagari, whereas the southern branch develops rounded, headline-free letterforms; Gujarati retains Devanagari letterform geometry while shedding the shirorekha.

Modern Devanagari has structural features with no Latin counterpart, and classical questioned-document methodology was codified on the Latin script [4–7]. Letters hang from a continuous headline (shirorekha); vowel signs (matras) occupy three distinct vertical zones; consonant clusters combine into conjuncts; and specific letters (अ, घ, भ, थ) deliberately break the headline. Latin-based examination frameworks therefore misalign when applied to Devanagari: they anchor to a baseline, while Devanagari geometry hangs from a headline. This study addresses that gap, using digital measurement in Digimizer image-analysis software to evaluate writer familiarity, state-level class characteristics, and cross-script transfer.

2. Background and review of literature

2.1. Foundations of handwriting individuality and forensic examination methodology

The scientific examination of handwriting rests on two linked premises: mature handwriting is habitual, and the habits a person accumulates across a sufficient body of writing are, in combination, effectively individual. Both premises were articulated in the discipline's foundational treatises.

Osborn [4] argued that questioned and known writing should be compared systematically, along writing movement, letter design, arrangement, and line quality, and insisted that identification rests on combinations of characteristics rather than isolated similarities. Harrison [5] moved this into the laboratory, treating handwriting as the product of a trained neuromuscular system whose deviations from the taught copybook model constitute the examiner's evidential material. Hilton [6] drew the now-standard distinction between class characteristics, shared by writers trained under a common system, and individual characteristics that depart from the taught model. Huber and Headrick [7] later consolidated the theoretical basis, cataloguing twenty-one discriminating elements of handwriting and framing examination as hypothesis testing between the propositions of common and different authorship.

Two empirical strands support these classical accounts. First, proficiency studies found that trained document examiners substantially outperform lay judges at writer identification, evidence that the examination is a genuine expertise rather than intuition [8]. Second, the individuality premise received large-sample quantitative validation when Srihari, Cha, Arora, and Lee [9] extracted computational features from the handwriting of 1,500 writers representative of the United States population, showing with high statistical confidence that writers can be discriminated from macro- and micro-level features of their writing. Crucially, this validation, like the classical treatises, was conducted entirely on the Latin script; its geometric assumptions (baseline anchoring, x-height zonation, ascender–descender architecture) do not transfer unmodified to headline-suspended scripts.

2.2. The Brahmi lineage and the structural anatomy of Devanagari

The writing systems of South Asia descend from Brahmi. Its earliest securely dated use, radiocarbon-dated sherds from Anuradhapura, Sri Lanka, reaches back into the early fourth century BCE [1]. Salomon [2] traces the palaeographic diversification of Brahmi into northern (Nagari) and southern branches. In the Nagari line, the proto-headline, originally a serif-like head-mark on individual letters, consolidated into the continuous shirorekha of Devanagari. The southern branch, written on palm leaf with a stylus, favored the rounded letterforms characteristic of Telugu, Kannada, Tamil, and Malayalam. Daniels and Bright [3] supply the standard typological account of Devanagari as an abugida: consonant graphemes carry an inherent vowel; other vowels appear as satellite matras positioned before, after, above, or below the consonant; and consonant clusters are written as conjuncts. For the forensic examiner, this history predicts which scripts share motor-spatial habits with Devanagari: Gujarati, Gurmukhi, and Bengali, all headline-bearing or recently headline-shedding northern scripts, and which do not, the rounded southern scripts. That structural contrast is the basis of the cross-script transfer examined in this study.

2.3. Class and individual characteristics of Devanagari and allied scripts

Forensic work directed specifically at Devanagari begins with Saxena and Singh [10], who classified the script's writing elements for examination purposes. Their inventory, the first systematic one for Devanagari, covers headline treatment, letter bodies, matra forms, and conjunct construction, and mirrors the Latin-script element catalogues of the classical literature. They showed that the shirorekha and its execution admit examiner-relevant variation: continuous versus fragmented, drawn before versus after the letter bodies, present versus omitted. The headline thereby became a legitimate locus of both class and individual characteristics.Later Indian work elaborated this inventory at the population level. Sorate, Kanwal, and Malhotra [11] compared Hindi and Marathi writing, two languages sharing the Devanagari script, and found systematic language-community differences in letterform selection and diacritic treatment within a single script: an early sign that "Devanagari" is not one homogeneous copybook population. Tyagi, Sankhla, and Kumar [12] analyzed class characteristics qualitatively in Devanagari samples from Northern India, documenting recurrent regional patterns in arrangement, slant, alignment, and letter design that group writers by schooling background. That work directly anticipates the state-cohort design (O1) of the present study.Sharma, Sharma, and Mahajan [13] compared Devanagari with Gurmukhi and Telugu, three scripts of common Brahmi origin, identifying shared class features (left-to-right direction, comparable letter inventories) alongside script-specific divergences (headline treatment, bowl geometry). They argued that such comparison lets examiners handle unfamiliar scripts by reference to their structural relatives.

2.4. Regional and population-level class characteristics

A parallel literature shows that a writer's training population leaves detectable class signatures even within a single script. Turner, Sidhu, and Love [14] examined class characteristics in the Gurmukhi handwriting of first- and second-generation Punjabi writers, finding generational differences traceable to differing exposure to formal Gurmukhi schooling. Their result was an early demonstration that familiarity gradients, not merely script identity, structure handwriting features. Turnbull, Jones, and Allen [15] identified class characteristics of Polish nationals writing in English: a writer's first training system persists as detectable class evidence in a second script, and examiners can, with defined error rates, assign writing to the Polish-trained population.Within India, Saini and Kaur [16] examined the English handwriting of writers from Andhra Pradesh, Punjab, and Kashmir, reporting state-level feature clusters strong enough to indicate a writer's regional schooling from English writing alone. Together these studies justify treating "population of training" as an examinable variable, and they supply the methodological template adopted here: frequency analysis of categorical features across defined cohorts.

2.5. Cross-script transfer and first-language influence

The mechanism behind such population effects is motor transfer: a writer acquiring a second script recruits the neuromuscular programmes trained by the first. Stewart [17] states the principle directly: a person beginning to write in a second language applies the motor and coordination skills of the first, and long-trained habits exert a persistent influence on all subsequent writing. In the Indian forensic literature, Singh, Gupta, and Saxena [18] demonstrated the evidential consequence. In simple forgeries, features of the forger's primary language and idiosyncratic first-script habits intrude into the simulated writing, giving examiners a source of identification that survives deliberate disguise.

Kaur, Garg, and Mahajan [19] systematically compared Gurmukhi and Latin scripts in handwriting identification, concluding that examination conventions calibrated on one script mislead when transferred to another. Their comparison is pertinent here because Gurmukhi shares Devanagari's headline architecture; it isolates exactly the baseline-versus-headline anchoring problem. Most recently, a review of multilingual handwriting analysis in forensic science [20] synthesized the challenges posed by bilingual and multilingual writers across Latin, Devanagari, Arabic, Chinese, Cyrillic, and Hebrew systems, observing that bilingual writers' habits shift with the language in use and that script-specific structural knowledge remains a precondition for valid comparison even as automated methods advance.

2.6. Computational writer identification in Indic scripts

A fast-growing pattern-recognition literature confirms, by independent means, that Devanagari carries writer-discriminating information. Halder, Thakur, Phadikar, and Roy [21] achieved writer identification from pre-segmented handwritten Devanagari characters, reporting that individual characters, and even matra modifiers, differ measurably in individuality, with identification accuracy varying by grapheme. Obaidullah, Halder, Santosh, Das, and Roy [22] released PHDIndic_11, a page-level handwritten document dataset covering eleven official Indic scripts written by 463 individuals, establishing benchmark infrastructure for script and writer identification research across the Brahmi family. Sethi, Kumar, and Jindal [23] advanced a hybrid framework combining convolutional neural networks with support vector machine and random forest classification for Devanagari writer identification, showing that learned features of the script support high-accuracy attribution.DohaScript, a large-scale multi-writer dataset of continuous handwritten Hindi text [24], extends this infrastructure from isolated characters to continuous writing, the level at which forensic parameters such as headline continuity, inter-word spacing, and pen-lift behaviour operate. These computational results are convergent evidence for the individuality premise in Devanagari, but they output classifier decisions rather than examiner-interpretable measurements. They therefore complement, rather than replace, a measurement framework expressed in the discipline's own feature vocabulary.

2.7. Synthesis: the research gap

Read together, the literature establishes four things. The individuality premise is validated, but on the Latin script [4,7,9]. Feature inventories exist for Devanagari and its relatives, but they are largely qualitative [10,12,13]. Training population, familiarity, and first script leave detectable traces, but the evidence comes principally from Latin or Gurmukhi contexts [14–16,18,19]. And Devanagari is demonstrably writer-discriminating, but in classifier terms external to forensic practice [21,23]. What is missing at the intersection is a quantitative, headline-anchored measurement framework, operationalized in examiner-accessible software, that jointly evaluates writer familiarity, state-level class characteristics, and graded cross-script transfer within Devanagari itself. The present study is designed to occupy that gap.

3. Aims, objectives, and hypotheses

The study pursued six primary objectives (O1–O6):

O1: trace the forensically relevant structural consequences of Devanagari, including state-level class characteristics across seven Indian states;

O2: compare writers formally schooled in Hindi/Devanagari with unfamiliar writers;

O3: compare frequent with infrequent Devanagari writers;

O4: compare writers whose natural signature is executed in Devanagari with those signing in another script;

O5: operationalize a headline-anchored measurement framework in Digimizer and assess its reliability;

O6: evaluate cross-script transfer between structurally similar (Gujarati, Gurmukhi, Bengali) and dissimilar (Telugu) first scripts.

Five directional hypotheses were specified in advance and evaluated at a familywise $\alpha =$ 0.05α=0.05 (Holm–Bonferroni corrected across the inferential family; Section 4.5):

H1: familiar writers exhibit higher headline continuity than unfamiliar writers.

H2: familiar writers exhibit lower slant dispersion.

H3: familiar writers execute fewer pen lifts per word.

H4: familiar writers place matras closer to conventional positions (smaller offset ratios).

H5: writers whose first script is structurally similar to Devanagari transfer Devanagari-consistent features more strongly than writers of a structurally dissimilar first script.

4. Materials and methods

4.1. Design and participants

A total of N=350N = 350N=350 active adult writers participated, divided into seven state cohorts of n=50n = 50n=50 according to the location of primary schooling (O1). Four cohorts came from states where Hindi/Devanagari is the medium of schooling and daily use: Uttar Pradesh, Rajasthan, Haryana, and Delhi/NCR, together forming the Devanagari-familiar group (n=200n = 200n=200). Three cohorts came from non-Hindi-speaking states: Andhra Pradesh, Kerala, and Tamil Nadu, forming the Devanagari-unfamiliar group (n=150n = 150n=150). The remaining grouping factors, frequency of Devanagari use (O3), signature script (O4), and first script (O6), are cross-cutting classifications of the same participant pool rather than mutually exclusive recruitment arms, so an individual participant could appear in more than one comparison group (for example, a familiar writer may also be a frequent writer).Written informed consent was obtained from all participants prior to sample collection, and all specimens were pseudonymized before measurement. Group composition and demographics are given in Table 2. An a priori sensitivity analysis indicated that groups of n=150n = 150n=150 and n=200n = 200n=200 provide 80% power to detect standardized mean differences of d≥0.30d ≥ 0.30d≥0.30 at two-tailed α=0.05α = 0.05α=0.05; all effects of primary interest substantially exceeded this threshold.

4.1.1. Inclusion and exclusion criteria

General criteria. Eligible participants were adults aged 18–60 years, a bracket chosen to ensure stable motor control while excluding developmental handwriting change at the lower end and age-related neuromuscular decline at the upper. Both right- and left-handed writers were eligible provided they had normal or corrected-to-normal vision and reported no motor, neurological, or hand–arm musculoskeletal disorder affecting handwriting (for example, tremor, arthritis, or dysgraphia). Participants were excluded if they were under the influence of alcohol or of medication affecting motor performance, or reported extreme physical fatigue, at the time of collection. Specimens were excluded if incomplete, smudged, or showing artificial distortion or deliberate disguise, and if written with non-standard instruments or surfaces.

Writing materials and sample text. Writing was executed with a standardized 0.7 mm blue ballpoint pen on standardized A4 80 GSM paper, unruled for natural baseline analysis and ruled for constrained baseline analysis. The dictation passage was a standardized text containing the full Devanagari varnamala, upper- and lower-zone matras, conjuncts and half-letters (samyuktakshar), numerals, and common words.

Objective-specific criteria.

Familiarity (O2). Group A comprised writers who studied Hindi as a compulsory or elective subject to at least Class 10 and write Devanagari natively or fluently. Group B comprised writers from non-Devanagari script states who had never studied Hindi or Devanagari in formal schooling and could not read or write Hindi fluently. Writers without formal Hindi schooling who had nonetheless acquired high Devanagari fluency through adult migration or occupational demand were excluded as a confound.

Frequency of use (O3). Frequent writers wrote in Hindi daily or weekly for professional, academic, or personal purposes; infrequent writers had passive knowledge of the script but wrote less than monthly, using English or a non-Devanagari regional script in daily life. Writers whose habits fluctuated seasonally and could not be assigned confidently to either category were excluded.

Signature script (O4). The Devanagari-signature group comprised writers whose legal signature on government identification or bank records is executed in Devanagari; the comparison group comprised those signing in Roman script, another regional script, or an abstract illegible stylization. Writers using hybrid or bilingual signatures, or who had changed signature script, were excluded.

Measurement framework (O5). A specimen was analysed only if it contained at least three continuous words with an intact or partially intact shirorekha permitting slant, alignment, and spacing measurement, and if it contained the designated structural test characters (अ, भ, थ, ध, क्ष), upper- and lower-zone matras, and half-letter conjuncts.

Cross-script transfer (O6). The similar-script cohort comprised writers whose first script is Devanagari-based or structurally close to it (Gujarati, Gurmukhi, Bengali); the dissimilar-script cohort comprised writers of rounded Dravidian scripts (Telugu) having fundamentally different stroke directions, circular movement patterns, and no headline structure. Writers raised in bi-scriptural households and fluent in both a similar and a dissimilar script from early childhood were excluded, as transfer effects would be confounded.

4.2. Writing task and specimen collection

Each participant was given the standard sample text in printed form and asked to copy it three times,each repetition on a separate A4 sheet (alternating ruled and unruled formats). Participants sat comfortably under ambient lighting and completed all three sheets in a single sitting using the standardized 0.7 mm blue ballpoint pen. Specimens were digitized on a flatbed scanner (Epson L3150) at 600 dpi and stored for measurement. A representative specimen is shown in Fig. 3.

Fig. 3. Representative specimen from the standardized dictation task, written on unruled A4 paper with a 0.7 mm blue ballpoint pen; the blank lower portion of the sheet is cropped. The passage opens with isolated varnamala characters, followed by a heading and a continuous prose passage containing upper- and lower-zone matras, conjuncts and half-letters, and numerals. Continuous multi-word writing of this kind is the level at which the Headline Continuity Index, inter-word spacing, and pen-lift frequency are defined.

4.3. Feature framework and measurement

Table 1 summarizes the operational framework, which integrates classical qualitative features of questioned-document examination with quantitative digital parameters. All quantitative parameters were measured in Digimizer image-analysis software (version 6.5.4; MedCalc Software Ltd., Ostend, Belgium) on the scanned specimens. The fitted shirorekha of each word served as the geometric reference: slant was measured as the acute angle between the principal vertical stem and the fitted headline; zonal heights were measured perpendicular to the fitted headline; the Headline Continuity Index (HCI) was computed as inked headline length divided by word width; and matra placement was expressed as the pre-posed stem offset divided by core height. Stroke-width variation (Wmax÷WminW_{max} ÷ W_{min}Wmax÷Wmin) on defined vertical stems was recorded as a static proxy for pen pressure; its interpretive limits are discussed in Section 6.5. The measurement operations are illustrated in Fig. 4.

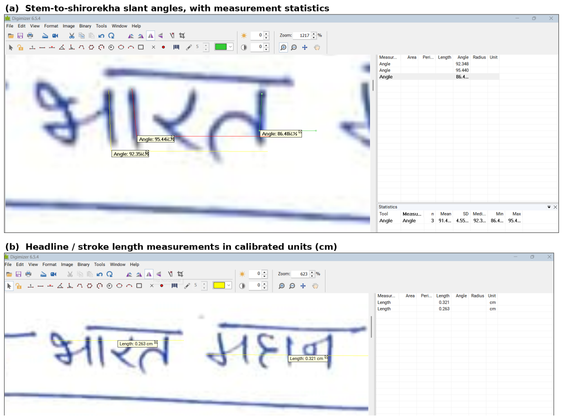

Fig. 4. Headline-anchored measurement workflow in Digimizer 6.5.4. (a) Stem-to-shirorekha slant measured with the angle tool at three consecutive stems of a single word, with the measurements list and descriptive statistics panel returning the per-sample mean and SD used as the slant-consistency index. (b) Length tool applied to headline and stroke segments in calibrated units, the operation underlying the Headline Continuity Index and the zonal and matra ratios. Values shown are illustrative of the measurement procedure on one specimen and are not group data.

4.4. Examiner reliability

All qualitative assessments and quantitative measurements were performed by a single examiner (N.T., a qualified questioned-document examiner), who was not blinded to group membership; the implications of single-examiner, non-blinded measurement are addressed in Section 6.5. Intra-examiner (test–retest) reliability was established by re-measuring a random 20% of specimens after a four-week interval for all retained quantitative variables. Two-way mixed-effects intraclass correlation coefficients (ICC, absolute agreement) ranged from 0.88 to 0.96.

4.5. Statistical analysis

Distributional assumptions were assessed with Shapiro–Wilk tests and inspection of Q–Q plots. Group comparisons used independent-samples t tests (df=348df = 348df=348) where distributional assumptions held and Mann–Whitney U tests otherwise; categorical feature frequencies were compared with χ2χ²χ2 tests (df=1df = 1df=1); and multi-group comparisons across states used one-way ANOVA (df1=6,df2=343df_1 = 6, df_2 = 343df1=6,df2=343). Effect sizes are reported as Cohen's d, rank-biserial correlation r, or Cramér's V as appropriate, and 95% confidence intervals of mean differences are reported for all t-tested variables. To control the familywise Type I error rate across the inferential family, Holm–Bonferroni correction was applied; all effects reported as significant remain so after correction. A linear discriminant analysis (LDA) with leave-one-out cross-validation (LOOCV) assessed the joint power of the strongest indices to assign writers to familiarity groups; equal prior probabilities were assumed and homogeneity of covariance matrices was assessed with Box's M test. All tests were two-tailed at α=0.05α = 0.05α=0.05. Statistical analyses were conducted in IBM SPSS Statistics (Version 29.0.1.0).

5. Results

5.1. Sample description and reliability

Demographic characteristics of the comparison groups and the pooled state cohorts are given in Table 2. Intra-examiner reliability was high across all retained quantitative variables (ICC = 0.88–0.96), supporting their use in the inferential analyses that follow.Pooling the state cohorts into macro-level familiarity groups needed justification, so an initial one-way ANOVA was run across all seven states of primary schooling (N=350N = 350N=350). Both the Headline Continuity Index (F(6,343)=28.42F(6, 343) = 28.42F(6,343)=28.42, p<0.001p < 0.001p<0.001) and slant consistency (F(6,343)=19.14F(6, 343) = 19.14F(6,343)=19.14, p<0.001p < 0.001p<0.001) varied significantly across states. Post-hoc Tukey HSD tests then split the seven states cleanly into two homogeneous subsets: Familiar (Uttar Pradesh, Rajasthan, Haryana, Delhi) and Unfamiliar (Andhra Pradesh, Kerala, Tamil Nadu). With no significant variation remaining within either subset, the cohorts were pooled into the Devanagari-familiar (n=200n = 200n=200) and Devanagari-unfamiliar (n=150n = 150n=150) macro-groups for all subsequent t-test and chi-square feature comparisons (df=348df = 348df=348).

5.2. Familiarity (O2) and frequency of use (O3)

Categorical feature frequencies for familiar versus unfamiliar writers are reported in Table 3 and displayed in Fig. 5. All five categorical markers discriminated strongly between the groups (χ2(1)≥108.21χ²(1) ≥ 108.21χ2(1)≥108.21, p<0.001p < 0.001p<0.001, V=0.556–0.702V = 0.556–0.702V=0.556–0.702), with native use of the purnaviram (।) the single strongest marker (χ2(1)=172.41χ²(1) = 172.41χ2(1)=172.41, V=0.702V = 0.702V=0.702).Quantitative indices are given in Table 4 and summarized in Fig. 6. Familiar writers wrote with steeper slant (81.4° vs. 74.2°; t(348)=9.315t(348) = 9.315t(348)=9.315, p<0.001p < 0.001p<0.001, d=1.01d = 1.01d=1.01) and markedly more consistent slant (SD 2.8° vs. 7.6°; U=655.0U = 655.0U=655.0, p<0.001p < 0.001p<0.001, r=0.956r = 0.956r=0.956). They also produced higher headline continuity (HCI 0.91 vs. 0.64; U=2530.0U = 2530.0U=2530.0, p<0.001p < 0.001p<0.001, r=0.831r = 0.831r=0.831), more compact upper-zone proportions (t(348)=−11.242t(348) = -11.242t(348)=−11.242, p<0.001p < 0.001p<0.001, d=1.17d = 1.17d=1.17), tighter matra offsets (U=1087.0U = 1087.0U=1087.0, p<0.001p < 0.001p<0.001, r=0.928r = 0.928r=0.928), and far fewer pen lifts per word (0.8 vs. 3.4; U=732.0U = 732.0U=732.0, p<0.001p < 0.001p<0.001, r=0.951r = 0.951r=0.951). The frequency-of-use contrast (O3) reproduced the same ordering of effects. These results support H1–H4; Fig. 8 compares the relative magnitude of the effects across both contrasts.

5.3. Signature script (O4) and cross-script transfer (O6)

Cross-script transfer metrics for writers whose first script is structurally similar to Devanagari (Gujarati, Gurmukhi, Bengali) versus dissimilar (Telugu) are reported in Table 5 and plotted in Fig. 7. Similar-script writers approached native performance on headline continuity (HCI 0.84 vs. 0.51; t(98)=9.487t(98) = 9.487t(98)=9.487, p<0.001p < 0.001p<0.001, d=1.89d = 1.89d=1.89, 95% CI [0.26, 0.40]) and stem verticality (84.2° vs. 71.6°; t(98)=9.207t(98) = 9.207t(98)=9.207, p<0.001p < 0.001p<0.001, d=1.83d = 1.83d=1.83, 95% CI [9.88, 15.32]). Telugu-first writers, by contrast, showed exaggerated bowl curvature (curvature index 1.42 vs. 1.08; t(98)=−11.946t(98) = -11.946t(98)=−11.946, p<0.001p < 0.001p<0.001, d=2.40d = 2.40d=2.40, 95% CI [-0.40, -0.28]), high slant dispersion (U=161.0U = 161.0U=161.0, p<0.001p < 0.001p<0.001, r=0.871r = 0.871r=0.871), and elevated pen-lift frequency (4.1 vs. 1.4 per word; U=93.0U = 93.0U=93.0, p<0.001p < 0.001p<0.001, r=0.926r = 0.926r=0.926). These results support H5.

5.4. Classification and discriminant analysis

An LDA model incorporating HCI, slant consistency, pen-lift frequency, and matra offset ratio achieved 92.6% overall LOOCV accuracy in assigning writers to the Devanagari-familiar versus Devanagari-unfamiliar groups (95% Wilson CI 89.1–94.7%). The homogeneity of covariance matrices assumption was assessed and met (Box's M = 14.63, p=0.152p = 0.152p=0.152). The classification sample comprised the full contemporary cohort: writers from the four Hindi-medium states (familiar, n=200n = 200n=200) and the three non-Hindi states (unfamiliar, n=150n = 150n=150). Sensitivity was 94.0% (188/200 correctly classified) and specificity 90.7% (136/150 correctly classified). The classification outcome is shown in Fig. 9. This performance quantifies group-level attribution of writer familiarity; it is not a measure of individual writer identification accuracy.

5.5. Hypothesis outcomes

All five pre-specified hypotheses were supported after Holm–Bonferroni correction: H1 (headline continuity: HCI 0.91 vs. 0.64), H2 (slant dispersion: SD 2.8° vs. 7.6°, r=0.956r = 0.956r=0.956), H3 (pen lifts: 0.8 vs. 3.4 per word, r=0.951r = 0.951r=0.951), H4 (matra offset: 0.12 vs. 0.28), and H5 (graded transfer: similar-script HCI 0.84 vs. dissimilar-script 0.51).

6. Discussion

From the results, it can be seen that Devanagari handwriting cannot be compared to traditional Latin-script baselines because it will result in systematic errors. The geometry of the Latin script is measured based on the baseline that acts as the most important point of reference from where measurements of x-height and ascenders are taken in an upward direction; while for Devanagari, the shirorekha acts as the most important mechanical and geometrical point of reference from where the body part comes down.

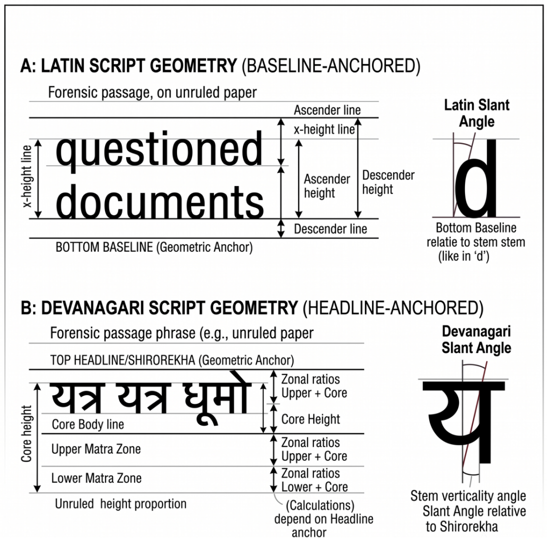

Fig. 2. Comparison of baseline-anchored Latin zonal geometry (A) with headline-anchored Devanagari zonal geometry (B). In Latin script the bottom baseline is the geometric anchor and slant is measured relative to it; in Devanagari the top headline (shirorekha) is the anchor, the core body is suspended beneath it, and upper- and lower-matra zones are measured perpendicular to the fitted headline. Stem verticality is therefore expressed relative to the shirorekha rather than to a baseline.

6.1. Headline continuity as a measure of familiarity

Headline continuity and execution order serve as strong measures of familiarity. Native and experienced writers show high headline continuity (HCI = 0.91), typically executing the shirorekha across whole word units after construction of the letter bodies. On the other hand, unfamiliar writers and writers favoring Telugu show discontinuous headlines (HCI = 0.51-0.64), executing the shirorekha for short parts letter-by-letter or leaving them unexecuted.

6.2. Hierarchical cross-script transfer

Hierarchical cross-script transfer depends on structural similarity. Cross-script transfer between scripts which share the same Brahmi-based spatial orientation and/or headline geometry (Gujarati, Gurmukhi, Bengali) transfers features that mimic the native execution of Devanagari, while the rounded form of the Telugu-first script creates unique native-script interference - with excessive curving of bowls and an unstable slant - consistent with previous reports of primary language influence on handwriting and forgery [13,18,19,25].

6.3. Evidentiary relevance

The proposed framework has direct evidentiary relevance. Under Sections 39 and 72 of the Bharatiya Sakshya Adhiniyam, 2023, expert handwriting opinion is admissible in court, and modern-day jurisprudence increasingly requires demonstrable reliability of any such opinion. Digital metrics validated in the study, such as Digimizer stem-to-headline measurements, facilitate the transition from estimation to reliable quantitative evidence in Devanagari handwriting examination. However, one must clearly state that the present research-level validation of the measurement framework only provides group-level reliability and discriminating ability; before its use in testimony, individual laboratories need to validate the measurements themselves and define the standard operating procedure with associated error rates, as required by OSAC/SWGDOC standards.

6.4. Scope of the classification model

The leave-one-out cross-validation (LOOCV) accuracy of 92.6% indicates how well the four indices classify the writers into the familiarity groups. This refers to the class-characteristic discrimination, similar to classification of writing into a training population. Individualization in casework depends on the combination of both class and individual characteristics examined by a qualified handwriting expert, and in this case, the present indices provide the quantitative support.

6.5. Limitations

Several limitations bound the interpretation of these findings. First, all measurements are static and offline: the stroke-width ratio is a proxy for pen pressure that is confounded by writing instrument, nib condition, paper absorbency, and scanning parameters, and it cannot substitute for instrumented capture of dynamic pressure and velocity. Second, all qualitative assessments and quantitative measurements were performed by a single examiner who was aware of each writer's group membership; although high test–retest reliability limits random measurement error, non-blinded single-examiner measurement cannot exclude expectancy bias, and blinded, multi-examiner replication is required before the reported effect sizes are treated as definitive. Third, all specimens were naturally written; the framework's behaviour under deliberate disguise, simulation, or tracing was not tested, and no claims are made here regarding forgery detection. Fourth, familiarity and frequency of use were partly self-reported and are therefore subject to classification error. Fifth, the indices were computed on multi-word passages; many questioned documents in casework consist of short entries or signatures, and the minimum quantity of writing required for stable estimates of HCI, slant dispersion, and pen-lift frequency remains to be established. Sixth, manual measurement in Digimizer retains an element of examiner dependence; high ICCs mitigate but do not eliminate this, and semi-automated headline fitting is a desirable development. Seventh, the state cohorts reflect location of primary schooling rather than lifetime residence, and the sample, though stratified, is not a probability sample of the Indian writing population. Finally, all data were collected and measured within a single laboratory; multi-laboratory replication, ideally with instrumented capture of dynamic features, is a natural extension.

7. Conclusion

Devanagari handwriting examination requires script-specific protocols rooted in its headline-suspended structure. By replacing baseline-dependent Latin metrics with headline-anchored digital measurements — the Headline Continuity Index, stem-to-shirorekha slant, and matra offsets, measured in Digimizer — examiners can reliably quantify writer familiarity, state-level class characteristics, and cross-script influence. Following laboratory-level validation and the establishment of minimum-sample requirements, these indices can support examination reports and expert testimony in a form suited to the reliability expectations accompanying the Bharatiya Sakshya Adhiniyam, 2023.

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Tables

Table 1. Feature framework for Devanagari examination, with operational definitions.

Domain	Feature	Operational definition / measurement	Type
Arrangement	Margins; line alignment; spacing	Margin widths (mm); orientation of fitted headline of each word relative to horizontal (uphill/downhill/level); inter-word gap ÷ core height	Class + quantitative
Headline (shirorekha)	Presence; continuity; execution order; extension; gaps	Headline Continuity Index (HCI = inked headline length ÷ word width); execution timing (before/during/after body); overshoot (mm); gap treatment at अ, ध, भ, थ	Individual + quantitative
Slant	Stem angle; slant dispersion	Acute angle between principal vertical stem and fitted shirorekha, measured via Digimizer angle tool; per-sample mean and SD	Quantitative
Zonation	Zone proportions	Heights of upper-matra, core, and lower-matra zones measured perpendicular to fitted headline; ratios upper ÷ core and lower ÷ core	Quantitative
Matras	Placement, angle, attachment	Pre-posed ि stem offset ÷ core height; angle of े / ै; attachment point of ु / ू; placement of anusvara and reph	Individual + quantitative
Conjuncts	Cluster construction	Selection for क्ष, त्र, ज्ञ, श्र and half-letters (half-form vs. explicit halant); vertical stacking vs. lateral joining	Class + individual
Letter design	Target letterforms	Variant selection and proportions of designated high-variability letters (e.g., jha, ṇa, la, śa) and numerals vs. copybook norms	Class + individual
Movement	Pen lifts; connections; strokes	Pen lifts per word (count); connections beyond headline; initial/terminal stroke form (blunt/tapered) and direction	Individual
Line quality	Fluency; tremor; retouching	Smoothness grading (1–5 scale); tremor presence; retouched stroke count per passage	Individual
Pressure proxy	Stroke-width variation	Ratio of maximum to minimum stroke width (Wmax ÷ Wmin) on defined vertical stems; static proxy only (see Section 6.5)	Quantitative
Punctuati	Marks;	Use of	Class

Domain	Feature	Operational definition / measurement	Type
on	digits	purnaviram (।) vs. period (.); Devanagari vs. international digits	
Errors	Matra and conjunct errors	Omitted, misplaced, or malformed matras and conjuncts (count per passage)	Group marker

Table 2. Group composition and demographics.

Group (objective)	n	Age, years (mean ± SD)	Sex (M/F)	Primary criteria / notes
Devanagari-familiar states (O2) a	200	34.2 ± 8.6	104/96	Uttar Pradesh, Rajasthan, Haryana, Delhi/NCR (n = 50 each); Hindi-medium schooling
Devanagari-unfamiliar states (O2) a	150	31.8 ± 7.4	82/68	Andhra Pradesh, Kerala, Tamil Nadu (n = 50 each); non-Hindi-medium schooling
Frequent writers (O3)	50	38.5 ± 10.1	25/25	Self-reported daily/frequent Devanagari writing
Infrequent writers (O3)	50	36.1 ± 9.3	27/23	Self-reported rare/never Devanagari writing
Devanagari signature (O4)	50	41.0 ± 11.2	30/20	Natural daily signature in Devanagari
Other-script signature (O4)	50	39.4 ± 10.5	29/21	Natural daily signature in Latin/other script
Similar first script (O6)	50	29.6 ± 6.8	24/26	Native writers of Gujarati (n = 18), Gurmukhi (n = 16), Bengali (n = 16)
Dissimilar first script (O6)	50	28.9 ± 6.2	27/23	Native writers of Telugu (n = 50)
Total contemporary sample	350	35.2 ± 9.1	186/164	Seven state cohorts of n = 50; O3, O4 and O6 groups are overlapping subsets of this pool

a Familiarity groups are defined by state of primary schooling (Section 4.1).

Table 3. Categorical feature frequencies by writer familiarity group.

Feature (category)	Familiar (%) (n = 200)	Unfamiliar (%) (n = 150)	χ^2 (df = 1)	p	Cramér's V
Headline drawn after letter bodies	72.0	14.0	115.71	< 0.001	0.575
Conventional headline gap preserved	84.0	26.0	119.33	< 0.001	0.584
Half-form conjuncts (vs. halant)	92.0	38.0	116.56	< 0.001	0.577

Feature (category)	Familiar (%) (n = 200)	Unfamiliar (%) (n = 150)	χ² (df = 1)	p	Cramér's V
Purna viram (।) used natively	88.0	18.0	172.41	< 0.001	0.702
Tapered terminal strokes present	78.0	22.0	108.21	< 0.001	0.556

Table 4. Quantitative indices by writer familiarity group.

Measure	Familiar (n = 200) (mean ± SD)	Unfamiliar (n = 150) (mean ± SD)	Test statistic (df = 348 unless specified)	p a	Effect size (d / r) b	95% CI of difference c
Slant vs. headline (°)	81.4 ± 4.2	74.2 ± 9.8	t = 9.315	< 0.001	d = 1.01	[5.68, 8.72]
Slant consistency (SD, °)	2.8 ± 0.9	7.6 ± 2.1	U = 655.0	< 0.001	r = 0.956	—
Headline Continuity Index (HCI)	0.91 ± 0.06	0.64 ± 0.18	U = 2530.0	< 0.001	r = 0.831	[0.24, 0.30]
Upper ÷ core zone ratio	0.48 ± 0.08	0.62 ± 0.15	t = -11.242	< 0.001	d = 1.17	[-0.16, -0.12]
Matra offset ratio (ि)	0.12 ± 0.03	0.28 ± 0.09	U = 1087.0	< 0.001	r = 0.928	—
Pen lifts per word (count)	0.8 ± 0.4	3.4 ± 1.1	U = 732.0	< 0.001	r = 0.951	[-2.77, -2.43]

a All effects remain significant after Holm–Bonferroni correction.
b Rank-biserial correlations (r) computed for Mann–Whitney U tests; Cohen's d computed for t-tests.
c 95% CIs of mean differences computed for variables utilizing t-tests.

Table 5. Cross-script quantitative transfer metrics (similar vs. dissimilar first script; n = 50 per group).

Measure	Similar script (Guj/Gur/Beng)	Dissimilar script (Telugu)	Test statistic (df = 98 unless specified)	p a	Effect size (d / r) b	95% CI of difference c
Headline Continuity Index (HCI)	0.84 ± 0.11	0.51 ± 0.22	t = 9.487	< 0.001	d = 1.89	[0.26, 0.40]
Slant consistency (SD, °)	3.9 ± 1.2	8.4 ± 2.6	U = 161.0	< 0.001	r = 0.871	—
Curvature index (bowl roundness)	1.08 ± 0.09	1.42 ± 0.18	t = -11.946	< 0.001	d = 2.40	[-0.40, -0.28]
Stem verticality angle (°)	84.2 ± 3.8	71.6 ± 8.9	t = 9.207	< 0.001	d = 1.83	[9.88, 15.32]
Pen lifts per word (count)	1.4 ± 0.6	4.1 ± 1.3	U = 93.0	< 0.001	r = 0.926	—

a All effects remain significant after Holm–Bonferroni correction.
b Rank-biserial correlations (r) computed for Mann–Whitney U tests; Cohen's d computed for t-tests.

c 95% CIs of mean differences computed for variables utilizing t-tests.

Figures

Figures 1 and 2 are schematic illustrations placed within the text at their first citation (Sections 1 and 6 respectively). Figures 5–9 below present the empirical data of Tables 3–5 and Section 5.4 in graphical form.

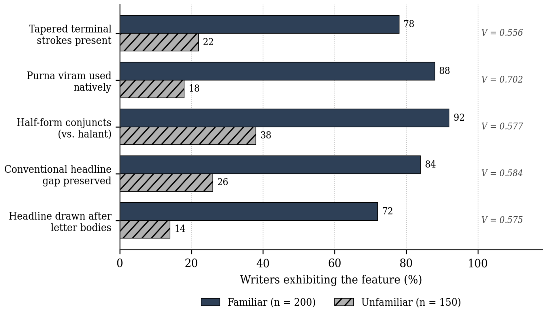

Fig. 5. Categorical feature frequencies by writer familiarity group (Table 3). Bars show the percentage of writers in each group exhibiting the feature; Cramér's V is given at the right of each pair. All five contrasts were significant at $\chi^2(1) \geq 108.21$, $p < 0.001$, and remained so after Holm–Bonferroni correction. Native use of the purnaviram was the single strongest categorical marker.

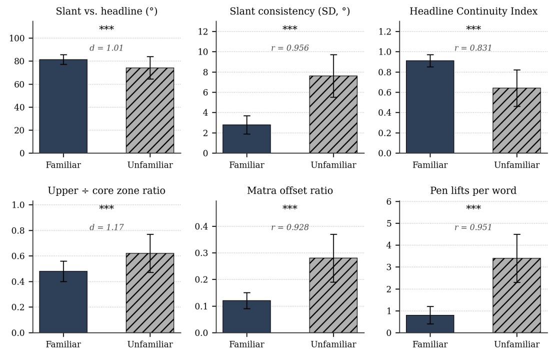

Fig. 6. Quantitative indices by writer familiarity group (Table 4). Bars show group means; error bars show ± 1 SD. Familiar writers (n = 200) are shown solid, unfamiliar writers (n = 150) hatched. Effect sizes are Cohen's d for t-tested variables and rank-biserial r for Mann–Whitney comparisons. *** $p < 0.001$ after Holm–Bonferroni correction.

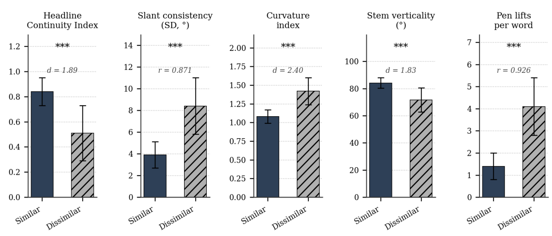

Fig. 7. Cross-script transfer metrics by structural similarity of first script (Table 5; n = 50 per group). Similar-script writers (Gujarati, Gurmukhi, Bengali) are shown solid; dissimilar-script writers (Telugu) hatched. Bars show means ± 1 SD. Telugu-first writers show the predicted native-script interference pattern: reduced headline continuity, elevated bowl curvature, unstable slant, and more frequent pen lifts. *** $p < 0.001$ after Holm–Bonferroni correction.

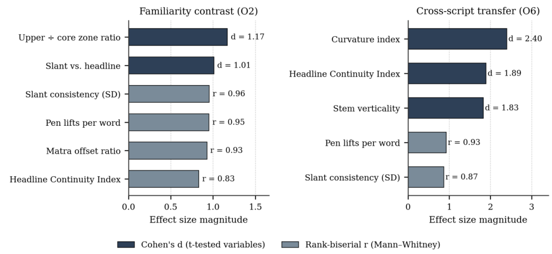

Fig. 8. Effect size profile for the familiarity contrast (O2) and the cross-script transfer contrast (O6), ranked by magnitude. Cohen's d and rank-biserial r are plotted on a common axis for visual comparison only; the two statistics are not on a common scale and their conventional interpretive thresholds differ ($d \geq 0.80$ and $r \geq 0.50$ are each conventionally 'large'). Every index in both contrasts exceeds its respective large-effect threshold.

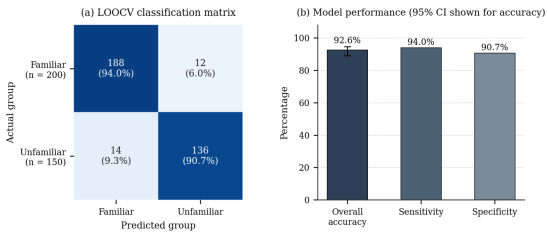

Fig. 9. Linear discriminant classification of writer familiarity using HCI, slant consistency, pen-lift frequency, and matra offset ratio (Section 5.4). (a) Leave-one-out cross-validated classification matrix; cell values give writer counts with row percentages. (b) Overall accuracy, sensitivity, and specificity, with the 95% Wilson confidence interval shown for overall accuracy. This is a group-level, class-characteristic determination and not an individual writer-identification error rate.