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Print ISSN: [3006-2497](#) Online ISSN: [3006-2500](#)Platform & Workflow by: [Open Journal Systems](#)<https://doi.org/10.5281/zenodo.23646421>**Pakistani English in the Age of AI: Which Features Are at Risk of Erasure?****Iftikhar Ali**

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Abstract

Large language models (LLMs) such as ChatGPT are now widely used in Pakistan to check, correct and “improve” English writing. Because these systems learn mainly from Inner-Circle English, they may treat legitimate features of Pakistani English as errors and replace them with American or British forms. This paper asks which features of Pakistani English are most at risk of such algorithmic erasure. Drawing on published descriptions of the variety, it compiles an inventory of 24 lexical, grammatical and discourse-pragmatic features and assesses each against three criteria: conflict with prescriptive Inner-Circle grammar, availability of a ready “standard” substitute, and cultural irreplaceability. The analysis identifies 13 high-risk, 9 medium-risk and 2 low-risk features. It argues that AI correction is likely to produce selective erasure: culturally specific vocabulary such as nikah or dupatta may survive as “local colour”, while the grammatical and pragmatic features that make Pakistani English a distinct system, such as stative progressives, invariant tags and deferential politeness formulae, are removed. Drawing on Irvine and Gal’s concept of erasure and on raciolinguistic perspectives, the paper interprets this as the automation of standard language ideology. It concludes with a testing protocol for empirical research and recommendations for teachers, universities and AI developers.

Keywords: Pakistani English; World Englishes; large language models; ChatGPT; erasure; standard language ideology; AI writing tools

1. Introduction

Since the public release of ChatGPT in November 2022, large language models (LLMs) have become everyday writing tools for students, teachers and professionals in Pakistan. A student asks the model to “correct the grammar” of an essay; a job seeker asks it to “make my cover letter more professional”; a lecturer pastes in a draft email to “improve” it. In each case, the model acts as an authority on what counts as good English.

In Pakistan, English is not just another subject. It is an official language, the medium of higher education, and the language of the courts, the civil service and most professional employment. Competence in English is closely tied to social class and opportunity (Rahman, 2002). For this reason, anything that changes how English is judged, taught or produced in Pakistan has consequences for who is seen as educated and employable.

This raises a question that is linguistic as well as social. Pakistani English is an established, institutionalised variety of English with its own vocabulary, grammar and discourse conventions (Baumgardner, 1993; Mahboob, 2004; Rahman, 1990). Its features are not random mistakes but systematic patterns shared by educated speakers. LLMs, however, are trained mainly on text from the United States and the United Kingdom. When such a model “corrects” Pakistani English, it may not be fixing errors at all, but replacing one legitimate variety with another.

Recent research shows that this concern is justified. LLMs have been found to make covertly prejudiced judgements about speakers of African American English (Hofmann et al., 2024) and to respond to non-“standard” varieties of English, including Indian English, with more stereotyping and condescension (Fleisig et al., 2024). AI-text detectors have also been shown to misclassify the writing of non-native speakers as machine-generated (Liang et al., 2023). To the authors’ knowledge, however, no study has asked which specific features of Pakistani English are vulnerable when AI tools edit Pakistani writers’ texts.

This paper addresses that gap. It is a descriptive and analytical study, not yet an experiment: it compiles an inventory of Pakistani English features from the published literature and assesses how likely each is to be erased by AI correction. It is guided by two questions:

Q1. Which features of Pakistani English are most at risk of being “corrected” or removed by AI writing tools?

Q2. What does the pattern of risk reveal about the language ideology built into these tools?

The paper is part of a wider doctoral project on how LLMs judge and rewrite Pakistani English, and it provides the feature framework that the project will test empirically.

2. Literature Review

2.1 Pakistani English as a Variety

English arrived in what is now Pakistan with British colonial rule and became the language of administration, law and elite education. After independence in 1947 it kept these functions alongside Urdu, and over the following decades it developed in contact with Urdu, Punjabi, Pashto, Sindhi and other local languages (Rahman, 1990, 2002). The result is a variety that shares its core grammar with other Englishes but has distinctive patterns in vocabulary, grammar, pronunciation and discourse.

In Kachru's (1985) Three Circles model, Pakistan belongs to the Outer Circle: countries where English, introduced through colonialism, has become an institutionalised second language with its own developing norms. Rahman (1990) provided an early linguistic description of Pakistani English, and Baumgardner (1990, 1993) documented its indigenised vocabulary and grammar. Mahboob (2004) described its morphology and syntax, and Mahboob (2009) showed how it carries local religious and cultural meanings, describing it as "English as an Islamic language". Many of its features are shared with other South Asian Englishes (Mesthrie & Bhatt, 2008).

These descriptions identify features at every linguistic level. At the level of vocabulary, Pakistani English borrows freely from Urdu and regional languages (*nikah*, *dupatta*), creates hybrid forms, coins new words (*prepone*) and extends the meanings of existing English words (*hotel* for a restaurant). At the level of grammar, it shows systematic differences in aspect, article use, question formation, tags and the use of particles. At the level of discourse, it has its own conventions for letters, requests and politeness, many of which reflect local norms of respect and hierarchy. Together, these features make Pakistani English a recognisable variety rather than a collection of individual errors.

Despite this body of description, Pakistani English is still widely treated as deficient English in schools, examinations and workplaces. Teachers and examiners often mark its features as errors against a British or American standard. The distinction between an *innovation* (a systematic, accepted variety feature) and an *error* (an individual learner's mistake) is therefore central. Bamgbose (1998) proposed that innovations gain legitimacy through demographic spread, use by educated speakers, codification and acceptability. Many Pakistani English features meet the first two criteria but lack codification, which leaves them open to "correction".

2.2 Standard Language Ideology and Erasure

Standard language ideology is the belief that one variety of a language is inherently correct and that others are deviations from it (Lippi-Green, 2012; Milroy & Milroy, 2012). It is maintained by institutions such as schools, dictionaries and publishers, and it treats prestige norms as natural rather than social. Irvine and Gal (2000) identified *erasure* as one of three semiotic processes through which language ideologies operate. Erasure is the process by which an ideology simplifies the sociolinguistic field, making some people, forms or practices invisible. In the case of Pakistani English, erasure occurs when its features are not seen as features at all, but only as errors to be removed. Raciolinguistic research adds that such judgements often depend less on the language itself than on the listener's perception of the speaker (Flores & Rosa, 2015).

2.3 AI as a New Language Authority

LLMs learn the patterns of their training data, which over-represents dominant groups and varieties (Bender et al., 2021). Research on bias in natural language processing has often failed to engage with sociolinguistics or with the communities affected (Blodgett et al., 2020). Hofmann et al. (2024) showed that LLMs can hold covert dialect prejudice even when they avoid overt bias, and Fleisig et al. (2024) found that model responses to eight non-"standard" Englishes contained more stereotyping, demeaning content and condescension than responses to standard varieties.

Studies of AI in Pakistan have so far focused mainly on whether tools such as ChatGPT improve learners' writing. These studies usually treat the AI's corrections as the target and do not ask whether those

corrections remove legitimate features of the local variety. This paper reverses the question: rather than asking how AI helps Pakistani writers approach a standard, it asks what Pakistani English loses in the process.

2.4 Research Gap

Three gaps emerge from this review. First, research on AI language bias has focused on American dialects and, to a lesser extent, on Indian English; Pakistani English has not been examined. Second, existing studies measure how models *judge* or *respond to* speakers of different varieties, but not which specific variety *features* are removed when models edit text. Third, research on AI in Pakistani education treats AI correction as beneficial by default and does not consider the variety being corrected. This paper addresses all three gaps by producing a feature-level assessment of the risks AI correction poses to Pakistani English.

3. Method

This is a qualitative, descriptive-analytical study. It proceeds in two steps.

3.1 Compiling the Feature Inventory

An inventory of 24 features was compiled from published descriptions of Pakistani English (Baumgardner, 1990, 1993; Mahboob, 2004, 2009; Rahman, 1990) and of South Asian Englishes more broadly (Mesthrie & Bhatt, 2008). Features were selected if they (a) are widely reported in educated Pakistani English usage, (b) occur in written as well as spoken English, and (c) differ from Standard American or British English. They were grouped into three levels: lexis, grammar, and discourse-pragmatics.

3.2 Assessing Erasure Risk

Each feature was assessed against three criteria, chosen because they reflect how AI correction is likely to work:

- C1. Prescriptive conflict:** Does the feature break a rule found in Inner-Circle reference grammars or usage guides? If so, a model trained to correct “grammar” is likely to treat it as an error.
- C2. Ready substitute:** Is there a common Standard English equivalent that can easily replace it? If so, replacement requires little effort from the model.
- C3. Cultural irreplaceability:** Does the feature name a concept with no close Standard English equivalent? If so, the model is more likely to keep it.

Features were then classed as **high risk** (C1 and C2 both apply), **medium risk** (no prescriptive conflict, but a ready stylistic substitute exists), or **low risk** (C3 applies, so no ready substitute exists). This classification is a reasoned prediction, not an empirical measurement; Section 6 sets out how it will be tested.

3.3 Scope

The study is limited to written Pakistani English, because AI writing tools act on written text. Pronunciation features, which are well documented for Pakistani English, are therefore excluded. The inventory is not exhaustive; it is a representative selection designed to cover the main linguistic levels at which erasure may occur. Both authors are speakers of Pakistani English, which helped in selecting features that are current in educated usage but also requires care to avoid treating every local form as standard.

4. Findings

4.1 The Feature Inventory

Table 1 presents the 24 features, with an illustrative example of each, its Standard English equivalent and its assessed risk level.

Table 1

Inventory of Pakistani English features and assessed risk of AI erasure

Level	Feature	Pakistani English example	Standard equivalent	Risk
Lexis	Coinage	The meeting has been <i>preponed</i> .	brought forward	High
Lexis	Kinship compound	my <i>cousin brother</i>	my (male) cousin	High
Lexis	Semantic shift	She <i>passed out</i> from Peshawar University.	graduated	High
Lexis	Semantic shift	Don't take <i>tension</i> .	Don't worry.	Medium
Lexis	Local term	<i>Load-shedding</i> lasted six hours.	power cut	Medium
Lexis	Semantic shift	We ate at a roadside <i>hotel</i> .	restaurant	Medium
Lexis	Religious formula	I will come, <i>Inshallah</i> .	God willing / hopefully	Medium
Lexis	Cultural borrowing	Their <i>nikah</i> is on Friday.	(no close equivalent)	Low
Lexis	Cultural borrowing	She wore a red <i>dupatta</i> .	(no close equivalent)	Low
Grammar	Stative progressive	I <i>am having</i> two sisters.	I have	High
Grammar	Invariant tag	You are coming, <i>isn't it?</i>	aren't you?	High
Grammar	Tense with <i>since</i>	I <i>am living</i> here since 2015.	have been living	High
Grammar	Plural non-count nouns	He gave me useful <i>informations</i> .	information	High
Grammar	Article use	He is <i>good doctor</i> .	a good doctor	High
Grammar	Prepositions and particles	We <i>discussed about</i> it; <i>cope up with</i>	discussed it; cope with	High
Grammar	Question without inversion	<i>What you are doing?</i>	What are you doing?	High
Grammar	Reduplication	Buy <i>small small</i> things.	a few small things	High
Grammar	Focus markers	Submit it <i>today itself</i> ; he came <i>yesterday only</i> .	today; only yesterday	High
Grammar	Modal <i>would</i>	I <i>would</i> come tomorrow at five.	will	High
Discourse	Salutation	<i>Respected Sir,</i>	Dear Sir,	Medium
Discourse	Request formula	<i>Kindly do the needful</i> .	Please take the necessary action.	Medium
Discourse	Greeting formula	<i>I hope you are fine</i> .	I hope you are well.	Medium
Discourse	Deferential request	<i>It is humbly requested that...</i>	I would be grateful if...	Medium

Level	Feature	Pakistani English example	Standard equivalent	Risk
Discourse	Letter closing	<i>Yours obediently,</i>	Yours sincerely / Kind regards	Medium

Note. Features compiled from Rahman (1990), Baumgardner (1990, 1993), Mahboob (2004, 2009) and Mesthrie and Bhatt (2008). Many are shared with other South Asian Englishes. Examples are illustrative. Risk levels are the authors' assessment using criteria C1–C3 (Section 3.2).

4.2 Distribution of Risk

Table 2 summarises the distribution. Of the 24 features, 13 (54%) are assessed as high risk, 9 (38%) as medium risk and only 2 (8%) as low risk.

Table 2

Distribution of erasure risk by linguistic level

Level	High	Medium	Low	Total
Lexis	3	4	2	9
Grammar	10	0	0	10
Discourse-pragmatics	0	5	0	5
Total	13 (54%)	9 (38%)	2 (8%)	24

High-risk features cluster in grammar. All ten grammatical features conflict with prescriptive rules and have ready substitutes. They include stative progressives (*I am having two sisters*), the invariant tag *isn't it?*, present tenses with *since* (*I am living here since 2015*), plural non-count nouns (*informations, advices*), reduplication (*small small things*), and the focus markers *itself* and *only* (*today itself*). Three lexical items are also high risk because their Standard English equivalents are obvious and their local meanings may be read as mistakes: *prepone*, *cousin brother* and *pass out* (meaning “graduate”), which a model may misread entirely as “faint”.

The concentration of risk in grammar matters because grammatical features are the most systematic part of a variety. Several of them are often linked to patterns in Urdu and other local languages: the invariant tag *isn't it?*, for example, works much like the Urdu tag *na*, and the wider use of progressive forms reflects how aspect is marked in local languages (Mesthrie & Bhatt, 2008). These features are therefore not careless slips but stable structures with a clear history. Because they also break rules found in prescriptive grammars, they are exactly the forms that a grammar-correction tool is designed to change.

Medium-risk features are mostly discourse-pragmatic. Formulae such as *Respected Sir*, *Kindly do the needful*, *I hope you are fine* and *Yours obediently* are not grammatically wrong, but when a user asks AI to make a text “more professional”, they are likely to be replaced with Inner-Circle conventions such as *Dear Sir*, *Please take the necessary action* and *Kind regards*. Lexical items with local meanings and ready equivalents, such as *load-shedding* (power cut) and *hotel* (restaurant), and religious formulae such as *Inshallah*, also fall into this group.

Low-risk features are culturally specific borrowings, such as *nikah* (Islamic marriage contract) and *dupatta* (scarf worn with *shalwar kameez*), that have no close Standard English equivalent and are therefore likely to be kept.

4.3 An Illustrative Rewrite

To show how these risks combine in practice, Table 3 presents a short job-application message written in Pakistani English, alongside the kind of rewrite that a request to “make this more professional” typically aims to produce. The rewrite is a constructed illustration for discussion, not the output of a particular AI model; testing actual model outputs is the purpose of the protocol in Section 6.

Table 3

Pakistani English original and a typical “professional” rewrite (constructed illustration)

Pakistani English original	“Professional” rewrite	Feature erased
<i>Respected Sir,</i>	<i>Dear Sir,</i>	Salutation
<i>I hope you are fine.</i>	<i>I hope you are well.</i>	Greeting formula
<i>I am having five years experience of teaching</i>	<i>I have five years of teaching experience</i>	Stative progressive
<i>and I passed out from University of Peshawar in 2018.</i>	<i>and graduated from the University of Peshawar in 2018.</i>	Pass out; article use
<i>I am living in Nowshera since my childhood.</i>	<i>I have lived in Nowshera since childhood.</i>	Tense with <i>since</i>
<i>Kindly do the needful and consider my application.</i>	<i>I would be grateful if you could consider my application.</i>	Request formula
<i>Yours obediently,</i>	<i>Kind regards,</i>	Letter closing

In this short message, eight features from Table 1 disappear in a single editing step: the salutation, the greeting formula, the stative progressive, *passed out*, the zero article, the present progressive with *since*, *Kindly do the needful* and *Yours obediently*. The rewritten text is fluent and acceptable, but it is no longer recognisably Pakistani English. Nothing in the rewrite tells the writer that their original was a legitimate variety rather than a list of mistakes.

4.4 The Pattern: Selective Erasure

The most important finding is not the number of features at risk but the shape of the risk. AI correction is predicted to keep the *vocabulary* of Pakistani culture while erasing the *grammar and pragmatics* of Pakistani English. A text that passes through an AI editor may still mention a *nikah* or a *dupatta*, but its sentences will follow American syntax and its politeness will follow Inner-Circle email etiquette.

This paper calls this pattern **selective erasure**. It reduces Pakistani English from a linguistic system to a set of decorative words, a kind of *cosmetic localisation*. What survives is the part of the variety that Inner-Circle speakers already accept as “exotic” vocabulary; what is lost is the part that shows Pakistani English to be a rule-governed variety in its own right.

5. Discussion

5.1 Erasure Automated

Irvine and Gal (2000) describe erasure as a process through which ideology renders inconvenient facts invisible. In the case of AI correction, this process is automated and repeated at scale. A teacher who marks *isn't it?* as an error affects one class; an AI tool that makes the same correction affects every user who asks it to improve their writing. The ideology is no longer only in the minds of individual teachers and examiners but is built into the tool itself, a phenomenon that can be called *algorithmic language ideology*.

Moreover, AI correction appears neutral. Users experience it as objective help rather than as the imposition of one variety's norms. This makes erasure harder to notice and harder to resist, because the norm that is being imposed is never named.

There is also a possible feedback loop. Texts edited by AI are published online, shared and reused, and may in time become part of the data from which future models learn. If AI-edited Pakistani writing contains fewer Pakistani English features, future models may see even less evidence that these features are legitimate, and correct them even more often. Erasure would then reinforce itself across generations of models.

5.2 Whose Norm?

Fleisig et al. (2024) found that LLMs default to Standard American English. If this holds for correction tasks, Pakistani writers who were taught British norms at school may find their English "corrected" not only away from Pakistani English but also away from British English, towards American spelling, vocabulary and conventions. The result would be a double displacement, and a further narrowing of global English towards a single centre.

5.3 Innovation or Error?

A fair objection is that not every non-standard form in Pakistani writing is a variety feature; some are genuine learner errors. This study does not claim that all corrections are illegitimate. The point is that AI tools currently have no way of distinguishing between the two: they apply a single external norm to both. Bamgbose's (1998) criteria suggest that features used consistently by educated speakers, such as those in Table 1, should be treated as innovations. Codifying these features in local dictionaries, style guides and AI evaluation sets would help both teachers and machines tell innovations from errors.

5.4 Consequences

Selective erasure has consequences beyond language. Pakistani students may learn to see their own English as faulty, increasing linguistic insecurity. Writers who do not use AI tools may be judged against texts that have been "Americanised" by AI. Over time, frequent AI editing could reduce the use of Pakistani English features in formal writing, weakening the codification the variety needs for recognition.

5.5 Implications for English Language Teaching in Pakistan

English language teaching in Pakistan has long been guided by British norms, while research on World Englishes has argued for recognising local varieties. AI tools add a new and powerful voice to this debate, and it is a voice that favours external norms. If teachers use AI feedback uncritically, they may reinforce the very attitudes that decades of World Englishes research have tried to change. On the other hand, AI corrections can become useful teaching material: comparing an original text with an AI rewrite is an

effective way to make students aware of the features of their own variety and of the choices involved in adapting to different audiences.

6. Proposed Testing Protocol

The risk classification in this paper is a set of predictions that can and should be tested. Table 4 outlines a protocol, which forms part of the authors' ongoing doctoral research.

Table 4

Proposed protocol for testing AI erasure of Pakistani English features

Component	Description
Materials	Short authentic texts (emails, essays, letters) each containing one or more Table 1 features, plus control texts with no variety features.
Models	Four to five widely used LLMs, with model version and test date recorded.
Prompt conditions	(1) "Correct the grammar"; (2) "Improve this text"; (3) "Make this more professional"; (4) "Correct only clear errors and keep Pakistani English features."
Repetitions	Each text and prompt run several times to account for variation in model output.
Measure	Retention rate: the proportion of runs in which each feature is kept unchanged; also, which substitute is used (American, British or other).
Analysis	Compare retention rates by feature level, risk class and prompt condition; check coding reliability with a second coder.

The paper's predictions can be stated as follows: (P1) retention rates will be lowest for high-risk grammatical features; (P2) "make it more professional" prompts will remove more discourse-pragmatic features than "correct the grammar" prompts; and (P3) culturally irreplaceable borrowings will be retained at the highest rate under all prompts.

7. Limitations

This study has three main limitations. First, its risk classification is based on reasoned criteria rather than on observed model behaviour, and some predictions may prove wrong; for example, newer models may be more tolerant of variety features than expected. Second, the inventory relies on published descriptions, some of which are several decades old, and Pakistani English continues to change. Third, the line between variety feature and learner error is not always clear, and some readers may disagree with the inclusion of particular features. These limitations point directly to the need for the empirical testing proposed in Section 6.

8. Recommendations

- **For students and writers:** when using AI tools, ask them to "correct only clear errors and keep Pakistani English features", and review each change rather than accepting all of them.
- **For teachers:** teach students the difference between variety features and errors, and use AI corrections as material for discussing language variation rather than as answer keys.
- **For universities and the HEC:** recognise Pakistani English as a legitimate variety in assessment guidelines and in policies on AI-assisted writing.

- **For AI developers:** include Pakistani and other South Asian Englishes in evaluation datasets, and offer correction modes that respect regional varieties.
- **For researchers:** test the predictions in this paper empirically, and build a codified reference list of Pakistani English features for use by teachers and machines.

9. Conclusion

This paper has argued that Pakistani English faces a new kind of pressure in the age of AI. By compiling 24 documented features and assessing their vulnerability to AI correction, it predicts that more than half are at high risk of erasure, and that the risk is unevenly distributed. Grammatical and pragmatic features, which mark Pakistani English as a system, are most vulnerable, while culturally specific vocabulary is most likely to survive. This *selective erasure* threatens to turn a living variety into decorative vocabulary inside American English sentences.

Whether this prediction holds is an empirical question, and the protocol in Section 6 provides a way to answer it. What is already clear is that AI writing tools are not neutral helpers. They carry language ideologies, and in Pakistan those ideologies may decide which English counts as “correct” for millions of writers.

Future research should test the predictions empirically across several models and prompt types, extend the inventory to other South Asian Englishes, and examine how Pakistani writers themselves respond when AI changes their English. Such work would help ensure that the spread of AI writing tools supports, rather than silences, the diversity of English as it is actually used around the world.

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