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THE AIDR-V INSTRUCTIONAL MODEL FOR DEVELOPING ENGLISH WRITING COMPETENCE AMONG GRADE 7-9 GRADE LEARNERS

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Abstract: *Generative artificial intelligence enables rapid, individualised feedback on second-language writing; however, the availability of automated feedback does not in itself constitute evidence of learning. The central pedagogical issue is how adolescent learners can interpret, evaluate, and use AI-generated recommendations while retaining authorship and avoiding dependence on automated correction. This theoretical and methodological study develops a human-centred GenAI instructional model for English as a foreign language (EFL) writing in Grades 7-9. It integrates research on automated writing evaluation, GenAI-mediated feedback, feedback uptake, self-regulated learning, formative assessment, AI literacy, and teacher mediation. These principles are operationalised through the five stages of the AIDR-V model: Activation, Inquiry, Drafting, Refinement, and Verification. The model assigns complementary responsibilities to the learner, teacher, and AI system. AI functions as a provisional diagnostic resource; the learner makes criterion- and evidence-informed revision decisions; and the teacher ensures pedagogical relevance, protects learner authorship, and calibrates assessment. The principal conceptual outcome is a reproducible lesson-level protocol that connects communicative purpose, CEFR-informed criteria, feedback classification, revision logs, independent verification, and reflective justification. Designed for specialised secondary schools in Uzbekistan, the model remains transferable across platforms and comparable educational contexts. Because a complete experimental dataset is not yet available, the study advances no causal claims regarding effectiveness. It concludes by formulating testable propositions and an evaluation framework for subsequent quasi-experimental validation.*

Keywords: *human-centred generative AI, EFL writing, feedback uptake, revision, verification, learner agency.*

7-9 SINF O‘ QUVCHILARINING INGLIZ TILIDA YOZISH KOMPETENSIYASINI RIVOJLANTIRISHDA AIDR-V INSTRUKSIONAL MODELI

Annotatsiya: *Generativ sun’iy intellekt boshqa tilda yozilgan matn bo‘ yicha tezkor va individuallashtirilgan qayta aloqa olish imkonini beradi; biroq avtomatlashtirilgan qayta aloqaning mavjudligi o‘ z-o‘ zidan o‘ rganish sodir bo‘ lganini anglatmaydi. Asosiy pedagogik masala o‘ smir o‘ quvchilarning SI tomonidan yaratilgan tavsiyalarni mualliflik nazoratini saqlagan va avtomatlashtirilgan tuzatishga qaramlikni yuzaga keltirmagan holda talqin qilishi, baholashi hamda qo‘ llashidan iborat. Ushbu nazariy-metodik tadqiqot 7-9 sinflarda ingliz tilida yozma nutqni o‘ rgatishga mo‘ ljallangan inson markazli GenSI instruksional modelini ishlab chiqadi. Unda avtomatlashtirilgan yozma nutqni baholash, GenSI vositasidagi qayta aloqa, qayta aloqani o‘ zlashtirish, o‘ zini o‘ zi boshqarib o‘ rganish, formativ baholash, SI savodxonligi va o‘ qituvchi vositachiligiga oid tadqiqotlar integratsiya qilindi. Mazkur tamoyillar AIDR-V modelining besh bosqichi - faollashtirish, izlanish, qoralama yaratish, takomillashtirish va verifikatsiya - orqali operatsionallashtirildi. Modelda SI dastlabki diagnostik vosita vazifasini bajaradi; o‘ quvchi mezon va dalillarga asoslangan tahrir qarorlarini qabul qiladi; o‘ qituvchi esa pedagogik muvofiqlikni ta’minlaydi, o‘ quvchi mualliflikini himoya qiladi va baholashni muvofiqlashtiradi. Tadqiqotning asosiy konseptual natijasi kommunikativ maqsad, CEFRga asoslangan mezonlar, qayta aloqa tasnifi, tahrir jurnali, mustaqil verifikatsiya va reflektiv asoslashni o‘ zaro bog‘ laydigan takror qo‘ llash mumkin bo‘ lgan dars protokolidir. Model O‘ zbekiston ixtisoslashtirilgan umumiy o‘ rta ta’lim muassasalari uchun ishlab chiqilgan bo‘ lsa-da, muayyan platformaga bog‘ lanmagan. To‘ liq eksperimental ma’lumotlar mavjud bo‘ lmagani sababli uning samaradorligi yuzasidan sababiy xulosalar chiqarilmadi; keyingi kvazieksperimental tekshiruv uchun sinovdan o‘ tkaziladigan farazlar va baholash mezonlari belgilandi.*

Kalit so‘ zlar: *inson markazli generativ SI; ingliz tilida yozma nutq; qayta aloqani o‘ zlashtirish; matnni tahrirlash; verifikatsiya; o‘ quvchi subyektligi*

ДИДАКТИЧЕСКАЯ МОДЕЛЬ AIDR-V РАЗВИТИЯ АНГЛОЯЗЫЧНОЙ ПИСЬМЕННОЙ КОМПЕТЕНЦИИ УЧАЩИХСЯ 7-9 КЛАССОВ

Аннотация: *Генеративный искусственный интеллект обеспечивает возможность быстрой и индивидуализированной обратной связи по письменным работам на втором языке; однако наличие автоматизированной обратной связи само по себе не свидетельствует об обучении. Ключевая педагогическая проблема заключается в том, как подростки могут интерпретировать, оценивать и применять сформированные ИИ рекомендации, сохраняя авторский контроль и не формируя зависимость от автоматизированного исправления. В настоящем теоретико-методическом исследовании разработана человекоцентричная учебная модель применения ГенИИ при обучении письму на английском языке в 7–9 классах. Модель интегрирует исследования по автоматизированному оцениванию письменной речи, обратной связи с использованием ГенИИ, освоению обратной связи, саморегулируемому обучению, формативному оцениванию, ИИ-грамотности и педагогическому посредничеству. Эти положения операционализированы в пяти этапах модели AIDR-V: активация, исследование, создание черновика, доработка и верификация. ИИ выполняет функцию предварительного диагностического ресурса; ученик принимает решения о редактировании на основе критериев и доказательств; учитель обеспечивает педагогическую релевантность, защищает авторство ученика и калибрует оценивание. Основным концептуальным результатом является воспроизводимый протокол урока, объединяющий коммуникативную цель, критерии CEFR, классификацию обратной связи, журнал редактирования, независимую проверку и рефлексивное обоснование. Модель разработана для специализированных общеобразовательных учреждений Узбекистана, но не зависит от конкретной платформы. Ввиду отсутствия полного массива экспериментальных данных причинные выводы об эффективности не формулируются; определены проверяемые гипотезы и рамка последующей квазиэкспериментальной валидации.*

Ключевые слова: *человекоцентричный генеративный ИИ; письмо на английском языке; освоение обратной связи; редактирование текста; верификация; учебная субъектность*

INTRODUCTION

Generative artificial intelligence has altered the conditions under which writing support is provided by making automated explanation, reformulation, error detection, and text generation available at the point of need. These affordances are particularly relevant to EFL instruction, in which learners require repeated opportunities to produce language and receive timely, comprehensible feedback. Technological availability, however, should not be conflated with a pedagogical mechanism. An AI system may identify an error or propose a fluent reformulation without ensuring that the learner understands the underlying problem, evaluates the recommendation, or transfers the revised form to a subsequent communicative task. The relevant educational question is therefore not merely whether AI can improve a text, but whether instructional design can transform AI-generated feedback into learner-controlled noticing, evaluation, revision, and sustained language development [Kasneci et al. 2023; UNESCO 2023].

This distinction is particularly consequential during adolescence. Learners in Grades 7–9 develop linguistic competence concurrently with metacognitive regulation, critical information practices, and a stable sense of authorship. Although they may value the speed and apparent authority of AI output, they may not yet possess sufficiently developed criteria for evaluating factual accuracy, pragmatic appropriateness, register, cultural relevance, and the validity of automated scores. Emerging school-based evidence indicates that younger learners may benefit from AI-supported language practice, but their engagement with feedback varies according to proficiency, task structure, feedback focus, and the extent of teacher scaffolding [Wu & Zhao 2025]. Accordingly, treating access to AI as an intervention in itself obscures the causal sequence linking feedback, learner uptake, revision quality, and subsequent performance.

Research on second-language writing has long shown that feedback becomes pedagogically meaningful only when learners act on it. Written corrective feedback may focus attention on linguistic form, but its value is mediated by comprehensibility, timing, learner beliefs, cognitive load, and opportunities for revision. Automated writing evaluation extends the scale and immediacy of feedback, yet earlier systems often prioritised surface-level accuracy and could produce opaque or decontextualised recommendations. Generative AI broadens feedback to organisation, coherence, vocabulary, argumentation, and audience awareness; at the same time, it increases the risks of hallucination, overcorrection, homogenised style, and substitution of machine production for learner production. These tensions make feedback uptake - not feedback generation - the more appropriate unit of pedagogical analysis [Ranalli 2018; Warschauer & Grimes 2008].

Human–AI collaboration provides a more pedagogically defensible basis for instructional design than replacement-oriented approaches. Teacher mediation can align automated feedback with curricular objectives, learner age and proficiency, genre requirements, and assessment criteria. Learner verification can, in turn, transform a suggested correction into an object of inquiry: the learner compares alternatives, consults an independent descriptor or reference source, records a decision, and explains the grounds for accepting, adapting, or rejecting the recommendation. Within this arrangement,

AI is neither positioned as an autonomous tutor nor treated solely as a prohibited shortcut; it functions as a provisional analytical resource within a pedagogically governed process. Human-centred frameworks developed by UNESCO and the British Council likewise emphasise agency, accountability, transparency, and the continuing authority of professional pedagogical judgement [Miao & Shiohira 2024; Felice et al. 2025].

A further research gap lies between broad principles of responsible AI use and reproducible classroom procedures. Policy and ethical guidance frequently remain at the level of general principles, whereas empirical studies may identify the digital tool without adequately specifying prompt protocols, feedback categories, revision sequences, teacher intervention, verification requirements, or implementation-fidelity indicators. Consequently, observed outcomes cannot readily be attributed to AI, additional time on task, teacher support, novelty, or the structured revision process. A model intended for school practice must therefore define the actors, sequence, criteria, and observable evidence required to determine whether the intervention was implemented as intended.

The present article addresses this gap by developing a human-centred GenAI instructional model within the AIDR-V lesson-design architecture: Activation, Inquiry, Drafting, Refinement, and Verification. It narrows the broader productive-skills framework to adolescent EFL writing because written production renders the sequence from initial drafting to feedback, revision, and verification directly observable. The study aims to formulate a theoretically grounded and operationally reproducible protocol for specialised secondary schools in Uzbekistan. It addresses three research questions: (1) How can AI-generated feedback support rather than displace learner authorship? (2) How should responsibilities be distributed among the learner, teacher, and AI system across the AIDR-V model? (3) Which process and outcome indicators are required for subsequent empirical evaluation?

The article offers three delimited contributions. First, it integrates feedback uptake, self-regulated learning, formative assessment, and AI literacy within a single lesson-level mechanism. Second, it specifies a five-stage protocol that can be implemented across different AI systems, thereby prioritising pedagogical functions over platform-specific features. Third, it formulates testable propositions and measurement requirements for a subsequent quasi-experimental study. Because the available dissertation materials do not yet include a complete experimental dataset, the reported results are confined to conceptual and methodological outputs: an instructional model, a distribution of roles, an implementation protocol, and an empirical-validation framework.

THEORETICAL FRAMEWORK

Feedback uptake as the central learning mechanism

Feedback may be defined as information that enables learners to reduce the discrepancy between current performance and an intended standard. In writing instruction, however, this discrepancy is not reduced through exposure to comments alone. Learners must identify the problem, interpret the feedback, evaluate its relevance, select an appropriate response, implement a revision, and assess the revised version. This sequence distinguishes the receipt of feedback from its substantive uptake. Although AI increases the volume and immediacy of available feedback, it does not remove these cognitive and metacognitive demands. Excessive, contradictory, or insufficiently prioritised recommendations may instead increase extraneous cognitive load and promote superficial compliance.

For the proposed model, feedback uptake is operationalised through observable revision behaviour. Each AI suggestion is assigned one of four learner decisions: accept, adapt, reject, or defer for teacher consultation. Acceptance means that the learner agrees with the recommendation and can provide a criterion-based reason. Adaptation means that the learner uses the underlying diagnosis but produces an independently worded solution. Rejection means that the learner identifies a defensible linguistic, pragmatic, factual, or genre-related reason not to apply the recommendation. Deferral is used when the learner recognises uncertainty and seeks human mediation. These categories make learner agency visible and prevent the final text from concealing how it was produced.

The quality of feedback uptake is analytically more informative than the proportion of accepted recommendations. A high acceptance rate may reflect accurate AI feedback, but it may also indicate dependence or uncritical compliance. Conversely, a well-justified rejection may demonstrate advanced language awareness. Evaluation should therefore establish whether the learner identified the focus of feedback, consulted an appropriate criterion, improved the text without distorting the intended meaning, and transferred the relevant principle to a subsequent task. From this perspective, revision constitutes evidence of learning rather than merely evidence of textual editing.

Learner agency, authorship, and self-regulation

Learner agency refers to the capacity to act intentionally, make choices, and assume responsibility within the constraints of a learning environment. In AI-supported writing, agency is threatened when the system determines the topic, generates the argument, selects the evidence, and produces the final language. It is strengthened when the learner establishes a communicative purpose, creates the initial draft, interrogates feedback, chooses revisions, and explains the final decisions. Authorship is therefore not defined by the absence of digital assistance; it is defined by meaningful human control over content, reasoning, expression, and revision.

Self-regulated learning provides a complementary account of how this control develops. Effective writers plan, monitor, evaluate, and adapt their performance. The AIDR-V cycle externalises these processes through a task brief, a draft, a feedback map, a revision log, and a reflective note. Externalisation is particularly important for adolescents because invisible metacognitive processes are difficult to teach or assess. By requiring evidence at each stage, the model allows the teacher to diagnose whether a learner's difficulty lies in language knowledge, interpretation of feedback, selection of strategy, verification, or reflection.

The teacher's role remains decisive. Human-centred AI requires more than the physical presence of a person; human purposes, professional judgement, and accountability must govern the use of the system. The teacher defines permissible uses of AI, selects or designs the prompt framework, models critical evaluation, limits the scope and volume of recommendations, resolves disputed feedback, protects personal data, and maintains alignment between assessment and the intended construct. Accordingly, the learner retains authorship, the teacher retains pedagogical accountability, and the AI system remains a fallible support resource.

Formative assessment and CEFR-informed criteria

Formative assessment is embedded in the cycle because feedback is used to modify ongoing learning rather than merely score a completed product. The CEFR Companion Volume provides a useful reference for communicative outcomes, but descriptors must be translated into age-appropriate task and rubric criteria. For a short argumentative or explanatory text in Grades 7–9, the assessment framework may include task fulfilment, organisation and coherence, lexical range and appropriateness, grammatical control, mechanics, and audience awareness. The purpose is not to treat the CEFR as a mechanical scoring algorithm; it is to ensure that feedback serves communicative performance rather than isolated error correction [Council of Europe 2020].

Automated scores should therefore be treated as diagnostic evidence rather than final judgements. AI systems may identify patterns warranting attention, but they may misinterpret creative language, multilingual influence, task-specific meaning, or culturally situated expression. The model consequently requires triangulation among learner self-assessment, teacher rubric-based assessment, and AI-assisted analysis. Divergence among these sources can be pedagogically productive when it becomes an explicit object of inquiry. The central validity question is not which evaluator is inherently superior, but which inferences each source of evidence can legitimately support.

MATERIALS AND METHODOLOGY

The study employs a design-oriented theoretical and methodological approach. Its evidence base comprises:

(a) international frameworks for human-centred and responsible AI in education;

(b) research on automated writing evaluation and GenAI-mediated feedback in EFL writing;

(c) studies of feedback uptake, learner engagement, and teacher - AI collaboration;

(d) CEFR-informed principles for communicative writing assessment;

(e) the instructional architecture developed within the author's DSc project for Grades 7-9 in specialised schools. Documentary analysis was used to identify recurrent design problems, and functional synthesis was applied to translate theoretical principles into observable classroom procedures.

The synthesis followed four analytical questions. First, which pedagogical function is assigned to AI: generation, diagnosis, explanation, adaptation, feedback, or assessment? Second, what learner action connects AI output with learning: noticing, comparison, revision, verification, reflection, or transfer? Third, what form of teacher mediation protects validity, age appropriateness, and authorship? Fourth, what evidence would allow another researcher to reproduce and evaluate the process? A design component was retained only when it answered all four questions.

The resulting model was evaluated conceptually against six criteria: pedagogical alignment, learner agency, feedback actionability, verifiability, assessment validity, and practical feasibility. Pedagogical alignment requires every AI action to support a stated communicative outcome. Learner agency requires an initial learner-produced draft and recorded revision decisions. Feedback actionability requires suggestions to be limited, prioritised, and understandable. Verifiability requires comparison with an independent source, descriptor, rule, model text, peer judgement, or teacher explanation. Assessment validity requires final judgements to remain rubric-based and human-calibrated. Practical feasibility requires implementation within ordinary lesson sequences and available school infrastructure.

This methodology yields a conceptual model rather than an estimate of intervention effectiveness. The present study therefore reports neither participant outcomes nor percentage gains, significance tests, or effect sizes. A subsequent empirical phase should preregister the primary outcome, define the comparison condition, establish scoring reliability, document implementation fidelity, and report adjusted effects with confidence intervals. Maintaining a clear distinction between model development and outcome evaluation prevents anticipated benefits from being represented as observed findings.

CONCEPTUAL RESULTS: THE AIDR-V INSTRUCTIONAL MODEL

Stage 1. Activation

Activation establishes communicative ownership before AI is introduced. The learner analyses the audience, purpose, genre, content requirements, and assessment criteria of the task. The teacher activates relevant language and background knowledge through a model, contrastive examples, or a short diagnostic activity. AI may generate alternative contexts or questions, but it must not produce the learner's response. The evidence generated at this stage includes a task interpretation, a brief plan, and a personal content inventory. These artefacts make it possible to determine whether the final text reflects the learner's intended meaning.

Stage 2. Inquiry

Inquiry develops the language and conceptual resources required for independent drafting. Learners examine how sample texts realise organisation, cohesion, stance, register, and audience awareness. They may ask AI to explain a feature, compare two alternatives, or generate a mini-practice item. The teacher models prompt boundaries and source checking. Inquiry ends with a learner-created checklist linked to the rubric. This stage prevents AI feedback from becoming the first encounter with the relevant criterion and reduces the risk that learners accept explanations they do not understand.

Stage 3. Drafting

Drafting is completed without sentence-level generative substitution. Learners produce an initial text using their plan and checklist. Permissible assistance may include access to a bilingual or monolingual dictionary, previously taught materials, and teacher-approved reference resources. The draft is preserved before AI interaction. This requirement is essential for authorship, baseline comparison, and analysis of revision. The teacher does not correct every error at this point; instead, the draft becomes the evidence base for diagnostic feedback.

Stage 4. Refinement

During Refinement, AI provides bounded feedback according to a teacher-designed prompt. The prompt identifies the learner's grade or proficiency band, the task, the rubric, the permitted feedback categories, and the prohibition against rewriting the entire text. Feedback is prioritised into a manageable number of high-value issues. For each issue, the learner records the original segment, the feedback focus, the AI suggestion, the decision category, the revised segment, and a brief reason. The teacher intervenes selectively where the AI recommendation is inaccurate, developmentally inappropriate, or inconsistent with the assessment construct.

Stage 5. Verification

Verification converts revision into critical language learning. The learner checks important recommendations against at least one independent criterion: a CEFR-informed rubric, an authoritative dictionary, a grammar reference, a teacher explanation, a model text, or structured peer review. Factual statements require an independent content source rather than confirmation from the same AI system. The learner then prepares a short reflective justification explaining which suggestions were accepted, adapted, rejected, or deferred and why. A revised text is considered complete only when the learner can account for consequential changes.

Role distribution within the cycle

Stage	Learner action	Teacher action	AI-system function	Process evidence
Activation	Defines purpose, audience, and content	Frames task and criteria	Provides contexts or diagnostic prompts	Plan and content inventory
Inquiry	Analyses models and builds a checklist	Models critical prompting and comparison	Explains features and supplies bounded practice	Learner-created criterion checklist
Drafting	Produces an independent first draft	Protects authorship and observes needs	No full-text generation	Archived initial draft
Refinement	Classifies and acts on feedback	Calibrates and corrects misleading feedback	Diagnoses and proposes limited revisions	Feedback map and revision log
Verification	Checks, justifies, and reflects	Validates decisions and assesses by rubric	Supports comparison but cannot independently validate its output	Verified draft and reflective note

DISCUSSION

The proposed model shifts analytical attention from the mere presence of AI to the instructional sequence within which it operates. This distinction is theoretically important because comparisons between AI-generated and teacher-provided feedback may overlook the learner actions occurring between feedback receipt and post-intervention performance. Accurate feedback that is neither understood nor applied may contribute less to learning than a smaller number of recommendations subjected to sustained evaluation and revision. AIDR-V therefore treats feedback uptake, revision quality, and verification behaviour as mechanism variables rather than incidental features of classroom implementation.

The model also establishes an explicit boundary between instructional assistance and generative substitution. It does not presuppose that every instance of text generation is pedagogically detrimental; instead, it requires the initial communicative content and first draft to originate with the learner. AI may support diagnosis, comparison, and refinement of expression, but the learner must retain control over claims, examples, organisation, and final wording. This principled boundary is preferable to an undifferentiated prohibition because it supports responsible participation in AI-rich learning environments while preserving assessable evidence of learner competence.

Teacher mediation is not an ancillary safeguard but a constitutive condition of pedagogical validity. Current AI systems cannot reliably account for the curriculum, the developmental profile of a particular class, the communicative purpose of a task, a learner's prior performance, or the construct being assessed. Teachers are also better positioned to identify instances in which formally correct feedback weakens authorial voice, alters intended meaning, or exceeds the learner's developmental needs. The teacher-in-the-loop configuration is therefore required not only on ethical grounds but also to protect the validity of instruction and assessment.

For specialised schools in Uzbekistan, the model has three practical advantages. First, it is compatible with CEFR-informed outcomes already used in foreign-language education. Second, it can be implemented with variable infrastructure because the core artefacts - a plan, draft, feedback map, revision log, and reflective note - do not depend on one platform. Third, it supports multilingual and culturally situated judgement: learners and teachers can reject recommendations that are pragmatically inappropriate or that erase locally meaningful content. Localisation therefore concerns tasks, criteria, examples, privacy, and interaction norms, not simply interface language.

Implementation nevertheless depends on explicit institutional conditions. Teachers require professional development in prompt design, feedback calibration, privacy protection, bias recognition, and interpretation of automated analyses. Schools require transparent policies governing user accounts, personal data, age-appropriate access, storage of learner work, and disclosure of AI assistance. Learners require explicit instruction regarding permissible forms of assistance, procedures for acknowledging AI use where required, and the principle that an AI-generated response cannot independently validate itself. In the absence of these conditions, the same technology may intensify superficial correction, unequal access, and learner dependence.

The model generates five testable propositions. P1: learners who complete the full feedback–revision–verification sequence will demonstrate greater gains in rubric-rated writing than learners who receive equivalent AI feedback without structured verification. P2: feedback-uptake quality will mediate the relationship between exposure to the intervention and improvement in writing performance. P3: justified adaptation and rejection decisions will predict transfer more strongly than the unqualified acceptance rate. P4: teacher calibration will reduce the proportion of inappropriate automated recommendations incorporated into final texts. P5: intervention effects will vary according to baseline proficiency, thereby requiring differentiated limits and scaffolds for feedback.

A later quasi-experimental evaluation should use intact Grade 7-9 classes while accounting for baseline differences. The primary outcome should be independently rated CEFR-aligned writing performance on a parallel task completed under controlled conditions. Secondary outcomes may include coherence, grammatical control, lexical appropriateness, feedback-uptake quality, revision accuracy, and learner agency, provided that each measure is specified in advance. At least two trained raters should score a subsample or all scripts, and inter-rater reliability should be reported. The main analysis should adjust post-test performance for baseline performance and report effect sizes with 95% confidence intervals.

Process evaluation is equally necessary. Fidelity indicators should record whether learners produced an independent draft, received feedback within the specified categories, completed revision logs, verified consequential recommendations, and received teacher calibration. Logs should distinguish intervention failure from theory failure: if verification was rarely completed, an absence of outcome differences would not constitute a valid test of the full model. Qualitative analysis of learner explanations can further reveal whether verification reflects genuine reasoning or formulaic compliance.

Several limitations must be acknowledged at the model-development stage. AI systems and their outputs change rapidly, which may render platform-specific claims obsolete. Revision logs may influence learner behaviour and increase workload. The quality of teacher calibration may vary across classes, while prior experience with AI and access outside

school may contaminate comparison conditions. Moreover, improvements in a final draft do not necessarily indicate durable learning. Transfer tasks completed without AI assistance are therefore essential to any subsequent evaluation.

CONCLUSION

The educational value of AI-generated writing feedback depends on the instructional actions through which learners and teachers interpret and use it. The AIDR-V model positions AI as a provisional diagnostic resource, the learner as author and decision-maker, and the teacher as instructional designer, mediator, and final pedagogical authority. Its five stages - Activation, Inquiry, Drafting, Refinement, and Verification - connect communicative purpose with independent production, bounded feedback, documented revision, source-based verification, and reflective justification. The contribution of the model is procedural rather than platform-specific: it operationalises human-centred AI principles as a reproducible sequence of classroom actions and observable evidence. For specialised secondary schools in Uzbekistan, the model provides a theoretically grounded means of integrating technological support with CEFR-informed assessment, academic integrity, and learner agency. The next research stage requires empirical validation through controlled writing tasks, a transparent comparison condition, inter-rater reliability analysis, fidelity monitoring, and effect estimates with confidence intervals. Until such evidence is available, the anticipated advantages of the model must remain testable propositions rather than claims of demonstrated effectiveness.

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