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Teacher and AI (Quillbot) Feedback on Students' Descriptive Essays: A Comparative Analysis

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ABSTRACT

This study examined how teacher feedback and AI-generated feedback from QuillBot influence the writing performance of Grade 11 students in descriptive essays. Corrective feedback was dominant for both evaluators, with the teacher providing 70.63% and QuillBot 91.33%, indicating a shared emphasis on grammatical accuracy and surface-level concerns. Grammar received the highest attention from both sources, with the teacher at 39.16% and QuillBot at 49.41%. Teacher feedback placed greater emphasis on clarity (29.37% vs. 15.46%), conciseness (11.19% vs. 4.45%), and tone (10.49% vs. 6.79%), while QuillBot prioritized fluency more strongly (23.89% vs. 9.79%). The teacher demonstrated broader pedagogical engagement through directive feedback at 27.97% and global-level feedback at 21.68%, whereas QuillBot concentrated on surface-level feedback at 88.76% with limited directive input at 5.15%. QuillBot also showed higher accuracy at 97.19% compared to the teacher at 88.81%. High application rates were observed for teacher feedback at 91.61% and QuillBot feedback at 87.82%, indicating strong student engagement. Overall, the findings suggest complementary roles, with teachers emphasizing higher-order writing features and AI strengthening linguistic accuracy.

Keywords: *teacher feedback, AI-generated feedback, QuillBot, writing performance, descriptive essay writing, Grade 11 students*

INTRODUCTION

Writing is not merely a technical skill; it is a powerful medium through which students explore ideas, construct meaning, and shape their academic and professional futures. Descriptive writing occupies a significant place in the curriculum because it develops students' ability to observe, analyze, and communicate experiences with clarity and precision. Unlike narrative or expository writing, descriptive writing requires learners to combine linguistic accuracy with creativity by selecting appropriate vocabulary, employing sensory details, and organizing ideas into coherent representations of people, places, objects, and events (Daffern & Mackenzie, 2020; Hamid et al., 2022).

Although students undergo formal English instruction throughout their basic education, many continue to encounter significant difficulties when composing descriptive essays. Barrot (2021) highlights that Filipino learners frequently struggle with maintaining coherence and cohesion, which disrupts the logical flow of ideas in their writing. Furthermore, the linguistic complexity of descriptive writing increases students' cognitive demands, making it difficult for them to produce coherent and effective texts (Paas & van Merriënboer, 2020; Crossley, 2020).

Feedback serves as a cornerstone in the development of writing competence. Teacher feedback provides individualized guidance that helps learners refine their ideas, improve their writing quality, and develop

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metacognitive awareness (Hyland & Hyland, 2019; Ene & Upton, 2018). However, providing detailed and personalized feedback remains challenging in classrooms with limited time and large class sizes. Students also need feedback literacy and evaluative judgment to effectively interpret and apply feedback (Carless & Boud, 2018; Tai et al., 2018).

Artificial Intelligence has emerged as a supplementary tool for writing support by providing immediate feedback on grammar, sentence structure, and word choice (Kessler, 2020). Automated Writing Evaluation (AWE) systems enable students to revise surface-level writing features independently while allowing teachers to focus on higher-order aspects of writing (Link et al., 2022; Luckin, 2018). Similarly, QuillBot promotes learner autonomy through paraphrasing and revision support (Li & Wilson, 2025; Ren, 2025). However, AI remains less effective in evaluating higher-order writing skills such as argumentation, creativity, and stylistic nuance (Abudalfa & Barrot, 2026).

To address this gap, the present study examines and compares teacher feedback and QuillBot-generated feedback on the descriptive essays of Grade 11 students. Specifically, it analyzes the feedback provided in terms of grammar, clarity, conciseness, tone, and fluency, as well as the types, levels, accuracy, and application of feedback. The study aims to provide practical insights into the complementary roles of teacher and AI-generated feedback and their potential integration into writing instruction.

Statement of the Problem

This study examined how teacher and AI (QuillBot) feedback affect the writing skills of Grade 11 students in the Reading and Writing subject focusing on their descriptive essays. Specifically, it seeks to answer the following questions:

1.What types of feedback do teachers and QuillBot provide on students' essays, and how frequently, in terms of:
   1.1. grammar;
   1.2. clarity;
   1.3. conciseness;
   1.4. tone; and
   1.5. fluency?
2. How do teacher and QuillBot feedback differ in terms of:
   2.1. types;
   2.2. level of detail;
   2.3. accuracy; and
   2.4. applications in revisions?
3. To what extent do teacher and QuillBot feedback identify and address similar or different writing issues in students' essays; and

4.What insights can be drawn from comparing teacher and AI feedback to enhance writing instruction?

METHODS

This study employed a comparative descriptive research design using quantitative content analysis to systematically compare the feedback provided by two teachers and the AI-powered writing tool, QuillBot, on the descriptive essays of 15 Grade 11 students in the Reading and Writing subject. The comparison focused on feedback types, total frequencies, levels of detail, linguistic accuracy, and application in student revisions across five writing components: grammar, clarity, conciseness, tone, and fluency. Quantitative content analysis was used to categorize, code, and record each feedback comment, while descriptive statistics, specifically frequency counts and percentage distributions, were applied to determine the prevalence and focus of the feedback. Comparative analysis was also conducted to identify similarities and differences between teacher-generated and AI-generated

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feedback in terms of structural depth, precision of corrections, and identified writing issues. physical drafts. The teacher feedback and QuillBot feedback were then organized and coded according to the five writing components: grammar, clarity, conciseness, tone, and fluency. The Feedback Analysis Matrix served as the central instrument for organizing and analyzing the feedback according to its source, writing component, type, level of detail, accuracy, application in revision, and remarks. Feedback was classified as global-level or surface-level based on Ferris (2002), with global-level feedback addressing higher-order concerns such as content, organization, coherence, and overall structure, while surface-level feedback focused on lower-order concerns such as grammar, punctuation, spelling, and word choice. The matrix enabled the researcher to systematically compare the characteristics of teacher-and QuillBot-generated feedback and examine how these forms of feedback were applied in students' revisions. After receiving feedback from both sources, the students revised their essays. The original and revised essays were examined to determine the extent to which the teacher- and QuillBot-generated feedback was applied in the revisions. All feedback entries were subsequently recorded in the Feedback Analysis Matrix, with each entry classified according to its source, component, type, level, accuracy, and application in revision. This procedure provided a systematic basis for comparing teacher-generated and AI-generated feedback across the established categories.

The collected data were analyzed quantitatively using frequency counts and percentage distributions. To provide a standardized basis for comparison, the total frequency of teacher-generated feedback was divided by two to obtain the arithmetic mean of the feedback provided by the two participating teachers, while the frequency of QuillBot-generated feedback remained unchanged. The adjusted teacher frequencies and QuillBot frequencies were then organized into tables and compared across the five writing components. The data were further analyzed according to feedback type, level of detail, accuracy, and application in student revisions. Comparative analysis was used to determine similarities and differences between teacher-generated and QuillBot-generated feedback based on the distribution and focus of feedback. The resulting frequencies and percentages provided a systematic quantitative basis for describing and comparing the characteristics of the two feedback sources.

RESULTS AND DISCUSSIONS

Frequency of Feedback Across Writing Components

Grammar

Both the teacher and QuillBot prioritized grammar, but QuillBot devoted a higher proportion of its feedback (49.41%) to grammatical corrections than the teacher (39.16%), indicating a stronger emphasis on rule-based linguistic accuracy.

Clarity

The teacher placed greater emphasis on clarity (29.37%) than QuillBot (15.46%), demonstrating a stronger focus on the comprehensibility and communicative effectiveness of students' writing.

Conciseness

The teacher allocated more feedback to conciseness (11.19%) than QuillBot (4.45%), reflecting a greater effort to eliminate redundancy and improve the economy of language.

Tone

The teacher provided more feedback on tone (10.49%) than QuillBot (6.79%), showing greater attention to stylistic appropriateness and contextual nuances in descriptive writing.

Fluency

QuillBot emphasized fluency (23.89%) more than the teacher (9.79%), indicating a stronger focus on sentence flow and rephrasing.

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A synthesis of the findings above aligns with previous literature highlighting the complementary strengths of teacher and AI feedback. The human teacher's balanced emphasis on grammar, clarity, conciseness, and tone supports the assertion of Al-Bashir et al. (2016) and AlGhamdi (2024) that teacher feedback plays a fundamental role in developing students' writing by providing meaningful ideas and recommendations that enhance understanding and communicative competence. The teacher's greater attention to clarity, conciseness, and tone reflects a pedagogical approach that extends beyond error correction to foster effective written communication. Conversely, QuillBot AI's stronger emphasis on grammar and fluency is consistent with Tong et al. (2021), who describe AI as an efficient analytical tool capable of delivering individualized and timely feedback that improves productivity. Nevertheless, the AI's comparatively limited attention to higher-order writing concerns demonstrates the constraints identified by Tong et al. (2021), particularly regarding the quality, authenticity, and emotional intelligence of its feedback. These differences indicate that each evaluator contributes distinct strengths to the writing revision process. Integrating teacher expertise with AI-assisted feedback may therefore provide students with more comprehensive support by combining pedagogical guidance with efficient linguistic analysis. Taken together, these findings suggest that while AI serves as an effective tool for enhancing linguistic accuracy and sentence fluency, teacher feedback remains indispensable for cultivating the broader communicative and pedagogical dimensions of writing.

Differences Between Teacher and QuillBot Feedback

Types of Feedback

Both evaluators primarily used corrective feedback, although QuillBot relied on it more heavily (91.33%) than the teacher (70.63%). The teacher also provided substantially more directive feedback (27.97%), while QuillBot occasionally offered suggestive feedback (3.51%) and no evaluative remarks. The observed differences in feedback distribution by types may be interpreted through the lens of social engagement in learning. According to Philp and Duchesne (2016), drawing on the interactional framework of Storch, effective learning occurs when learners actively engage with others by exchanging ideas and responding to feedback. The teacher's substantial use of directive feedback (27.97%) and occasional evaluative feedback (1.40%) suggests an effort to guide learners beyond error correction toward meaningful revision and improvement. Such feedback encourages interaction, reflection, and engagement with the learning process. In contrast, QuillBot's overwhelmingly corrective feedback (91.33%) focuses primarily on identifying and correcting linguistic errors, offering limited opportunities for the dialogic and socially mediated exchanges emphasized by Philp and Duchesne (2016). Consequently, while AI feedback may efficiently address surface-level writing concerns, teacher feedback appears better aligned with interaction-based learning principles that promote deeper learner engagement.

Level of Detail

Both sources mainly focused on surface-level feedback, but the teacher provided more global-level feedback (21.68%) than QuillBot (11.24%), demonstrating greater attention to organization and overall writing development. A claim that is being supported by Younas (2025) and Wang (2026) highlighting that AI-driven tools provide immediate feedback on grammatical accuracy, vocabulary, and other surface-level linguistic features, improving the efficiency of the revision process. However, human teachers remain indispensable for evaluating higher-order writing concerns, including organization, coherence, audience awareness, and pedagogical appropriateness, which require contextual and holistic judgment.

Accuracy

QuillBot achieved a higher accuracy rate (97.19%) than the teacher (88.81%), while the teacher showed higher rates of partially inaccurate and inaccurate feedback. However, teacher feedback remained more adaptable to students' individual needs. Nevertheless, this high level of technical consistency must be weighed against the built-in limits of AWCF (Automated Writing Corrective Feedback) systems. As highlighted in recent literature, AWCF is strictly limited to pre-programmed error types and the rigid functions of specific software engines.

Because it relies on these fixed rules, it lacks the flexibility needed to handle individual learner differences (Ranalli, 2018; Yoon et al., 2023). For example, automated software often relies on generic rubric templates or strictly follows standard American essay styles, which limits its usefulness across different writing contexts (Yoon et al., 2023). Therefore, while QuillBot successfully eliminates the technical slips and human errors caused by teacher fatigue, it relies on a rigid, machine-like uniformity. In contrast, even though the human teacher's feedback is more prone to minor mistakes due to exhaustion, it keeps a unique advantage: it can change its form, focus, and scope to match what the student needs, which automated systems simply cannot reproduce (Woodworth & Barkaoui, 2020).

Applications in Revisions

Students applied teacher feedback more frequently (91.61%) than QuillBot feedback (87.82%), suggesting greater trust and acceptance of teacher-generated guidance during revision. This trend points to a higher degree of student trust, perceived authority, or conceptual clarity regarding instructions issued directly by the human classroom instructor. This student behavior directly aligns with the warnings of Lin and Crosthwaite (2024), who argue that AI generated feedback often lacks deep contextual understanding and can provide formulaic or redundant suggestions that students choose to bypass. Furthermore, as Teng (2024) notes, automated tools carry a risk of providing inaccurate or confusing responses that hinder comprehension, which logically explains why learners in this study were more likely to reject or ignore the algorithmic interventions in favor of human guidance.

Similarities and Differences Between Teacher and QuillBot Feedback

First, the findings reveal a high level of convergence at the surface level, as both evaluators positioned rule-based technical mechanics as their top priority. QuillBot dedicated 49.41% of its total feedback to grammar corrections, while the teacher allocated a lower yet still dominant 39.16% to the same component. This alignment shows that both sources function effectively as surface-level screeners, relying heavily on direct corrective feedback to fix localized linguistic errors right on the page rather than leaving abstract comments. This convergence aligns with recent findings that AI-driven tools provide immediate feedback on grammatical accuracy, vocabulary, and other surface-level linguistic features, improving the efficiency of the revision process. However, human teachers remain indispensable for evaluating higher-order writing concerns, including organization, coherence, audience awareness, and pedagogical appropriateness, which require contextual and holistic judgment (Younas, 2025; Wang, 2026).

Second, a sharp contrast emerges when moving from mechanical accuracy to broader structural and stylistic development. The human teacher focused heavily on overall essay meaning and organization, making communicative clarity their second-highest priority at 29.37% and providing double the global-level feedback of the AI (21.68% versus 11.24%). In contrast, QuillBot bypassed these elements to focus on localized sentence smoothing, making fluency its second-highest priority at 23.89% while largely overlooking tone and conciseness, which require human cognitive abstraction to evaluate. This major divergence directly aligns with the assertions of Link et al. (2022), who noted that while automated software is highly effective at screening surface level errors like grammar, punctuation, and spelling, it fundamentally lacks the capacity for macro level evaluation. Consequently, delegating these mechanical tasks to a computer allows the human teacher to focus their specialized efforts on higher order writing skills.

Finally, the data highlights a compelling relationship between execution precision and instructional authority. QuillBot demonstrated superior technical precision with a 97.19% accuracy rate compared to the teacher's 88.81%, confirming that automated tools maintain a more consistent standard than human grading, since humans are prone to making mistakes when they get tired. However, students displayed higher compliance with the human instructor, successfully applying 91.61% of teacher-led interventions compared to 87.82% for QuillBot, which indicates that student revision behavior is ultimately driven by interpersonal trust and classroom authority rather than pure algorithmic accuracy. This outcome contradicts the findings of Tran (2025), which indicated that students engaged more frequently with revisions when provided with AI generated feedback compared to teacher generated feedback alone.

Implications for English Language Teaching

The following insights provide concrete, data-driven frameworks aimed at optimizing the division of labor between human cognition and automated sentence processing to enhance student writing development.

Implementation of a Dual Tiered Writing Assessment Framework

Educational institutions should restructure the writing process by adopting a dual tiered feedback framework that optimizes the distinct diagnostic strengths of both evaluators. Given that QuillBot AI demonstrated a high technical precision rate of 97.19% and handled the vast majority of surface level grammar interventions, students should utilize the AI tool as an initial screening mechanism. Passing initial drafts through the software allows students to eliminate rule based mechanical errors before submitting their work for human evaluation. This systematic division of labor ensures that student essays are mechanically clean upon teacher receipt, thereby maximizing the utility of manual grading. This localized division of labor aligns closely with broader trends in writing instruction. For instance, Mizumoto and Eguchi (2023) examined ChatGPT's role in automated essay scoring for L2 learners, demonstrating that AI-driven features can enhance scoring accuracy and provide effective corrective feedback. This baseline reliability was further solidified by Mizumoto et al. (2024), who validated AI's capability in assessing linguistic accuracy against human evaluators and Grammarly. The strong correlation found between AI assessments and human evaluations underscores its reliability, providing robust empirical support for integrating high-precision AI feedback as the primary tier in a dual-feedback model.

Strategic Shift Toward Higher Order Pedagogical Intervention

English language instructors should consciously recalibrate their feedback priorities to focus primarily on macro level writing components. Because the data indicates that the human teacher allocated 21.68% of interventions to global level structures and 29.37% to communicative clarity, teachers should delegate local sentence smoothing tasks to automated tools. Classroom instructional time and manual grading rubrics should minimize time spent flagging repetitive grammatical slips. Instead, instructors should dedicate their specialized pedagogical real estate to teaching cognitive abstraction, conceptual development, structural organization, and thematic clarity, which are areas where human evaluators maintain a distinct pedagogical advantage. This strategic delegation is supported by Su et al. (2023) demonstrating that platforms like ChatGPT can utilize evaluation rubrics to assess and provide feedback on students' argumentative writing, suggesting that such technology serves as a valuable supplement to traditional teacher-led corrective feedback. Similarly, Harunasari (2023) highlighted the capacity of ChatGPT to support the L2 writing process through tasks such as brainstorming, error detection, and proofreading. Collectively, these studies express optimism regarding the role of generative AI as a scaffolding tool, offering a strong rationale for instructors to delegate mechanical corrections to these platforms, thereby reserving their own expertise for more impactful, higher-order pedagogical interventions.

Leveraging Affective and Directive Authority for Revision Compliance

Instructors should consciously exploit their unique affective and directive authority to boost student revision compliance. The findings revealed a significantly higher student application rate of 91.61% for teacher led feedback compared to 87.82% for the AI, a trend directly linked to the teacher's strategic use of 27.97% directive feedback and constructive commentary. These results underscore that machine algorithms cannot replicate the explicit, context-rich directions and evaluative validation inherent in human teaching. This evidence aligns with the broader discourse on feedback uptake; likewise, few studies have compared students' responses to the two feedback sources. Notably, Zhang and Hyland (2022) explored students' revision operations based on teacher and automated writing evaluation feedback and found that teacher feedback was highly valued by students and had a higher uptake rate. Similarly, link et al. (2022) reported that students made more revisions based on teacher feedback than automated writing evaluation feedback, a result also corroborated by Tian and Zhou (2020), who found that teacher written corrective feedback consistently achieved a higher uptake rate than automated writing evaluation feedback. Ultimately, by wrapping technical corrections in supportive pedagogical dialogue, educators maintain the interpersonal trust and motivation required to drive successful student revisions, confirming that the teacher's presence is an essential catalyst for deep learning that technology alone cannot provide.

CONCLUSIONS

1. Both the human teacher and QuillBot AI effectively identified grammatical errors in students' descriptive essays, demonstrating their capability to improve students' linguistic accuracy. However, the human teacher adopted a more balanced approach by addressing clarity, conciseness, and tone, while QuillBot primarily focused on grammar and fluency.

2. Teacher feedback and QuillBot feedback differed substantially in their delivery and scope. Although QuillBot provided highly accurate and predominantly corrective feedback on surface-level writing issues, the human teacher offered more directive, global, and pedagogically meaningful feedback that addressed organization, coherence, and overall communicative effectiveness.

3. The human teacher and QuillBot exhibited complementary strengths in evaluating students' writing. While both consistently identified localized linguistic errors, the teacher demonstrated greater capability in addressing higher-order writing concerns that require contextual understanding, whereas QuillBot excelled in efficiently detecting and correcting mechanical language errors.

4.The integration of teacher and AI feedback provides a more effective approach to writing instruction than relying on either source alone. QuillBot serves as an efficient tool for preliminary linguistic screening and technical corrections, while teacher feedback remains indispensable for developing students' higher-order writing skills, critical thinking, and overall communicative competence. Consequently, combining AI-assisted feedback with teacher guidance offers a more comprehensive and pedagogically sound framework for improving students' descriptive writing performance.

Recommendations

Educators are encouraged to adopt AI tools like QuillBot as preliminary technical auditors. By allowing AI to handle the initial volume of grammar and fluency corrections, instructors can redirect their pedagogical focus toward mentoring students on higher order writing concerns, such as thematic development and voice. This shift in instructional priority can help prevent teacher burnout by automating repetitive mechanical checks. Furthermore, school administrators should consider providing professional development workshops that train teachers on how to integrate these digital tools into their existing feedback workflows without compromising academic integrity.

It is also recommended that curriculum developers incorporate AI assisted drafting phases that emphasize critical evaluation. These programs should include specific modules that teach students to analyze AI suggestions rather than accepting them passively. By treating AI output as a subject for debate rather than an absolute correction, students can develop a more sophisticated understanding of linguistic choices. Additionally, assessment rubrics should be updated to reflect this new reality, perhaps by rewarding a student's ability to justify why they accepted or rejected specific AI suggestions during the revision process.

Students should be instructed to utilize AI platforms as sophisticated proofreading tools rather than primary authors. The goal should be to use technology to polish the mechanical aspects of a manuscript while ensuring that the final work retains an authentic and purposeful tone. This practice encourages students to critically evaluate AI-generated suggestions instead of accepting them automatically, allowing them to make informed decisions about which revisions best align with their intended message. By maintaining active involvement throughout the revision process, students can preserve their individual voice while benefiting from AI's ability to improve grammar, clarity, and overall writing quality. In this way, AI serves as a supportive learning tool that enhances students' writing without diminishing their originality, critical thinking, or ownership of their work. Finally, future researchers should investigate the longitudinal impact of AI feedback on student writing autonomy. It is essential to determine whether prolonged exposure to AI corrections leads to improved independent writing skills or creates a dependency that hinders cognitive development. Further studies could also explore how feedback accuracy varies across different writing genres, such as creative narratives, research projects, or professional business communication, to determine the full extent of its instructional utility. Researchers might also look into the socio-economic implications of these tools, ensuring that the benefits of AI mediated feedback are accessible to all students regardless of their access to premium digital resources.

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