V Congreso en Docencia en Educación Superior Codes y I Congreso Latinoamericano y del Caribe de Innovación en Investigación en Educación Superior LatinsoTl La Serena, Chile. 8,9 y 10 de noviembre del 2023

DOI: https://doi.org/10.15443/codes2019

# Types of automated feedback on academic writing: first results from a comparative case description[1]

Javier Obreque[1[0009-0004-6077-665X]], Ignacio Lobos[2[0009-0007-7214-1880]], Marjory Astudillo[3[0009-0006-5056-6100]] and Karin Arismendi[4[0009-0007-7177-9209]]

[1] Fundación Instituto Profesional Duoc UC. Valparaíso, Chile.
j.obreque@profesor.duoc.cl
[2] Fundación Instituto Profesional Duoc UC. Valparaíso, Chile.
i.lobosm@profesor.duoc.cl
[3] Fundación Instituto Profesional Duoc UC. Valparaíso, Chile.
mar.astudillof@profesor.duoc.cl
[4] Fundación Instituto Profesional Duoc UC. Valparaíso, Chile.
k.arismendi@duoc.cl

**Abstract.** The purpose of this article is to present the preliminary results of an ongoing project that aims to describe, compare, and determine the scope of types of writing feedback, particularly academic, that can be provided automatically by freely available computational tools.
Specifically, the preliminary results of the analysis of four computational tools are presented: an artificial intelligence (ChatGPT 3.5) and specific academic writing support tools (ArText, Estilector, and PEUMO). The methodological approach employed identifies the type of feedback they provide based on the categories proposed by Alvarez *et al*. (2011) and Guasch *et al*. (2013), which include corrective, epistemic, suggestive, and epistemic-suggestive.

**Keywords:** Feedback, computational tools and academic writing.

## 1 Introduction

Academic writing involves composing written texts by individuals who belong to the same field, with their primary audience being members of the same academic-disciplinary area (Carlino, 2005). This practice is mainly developed within teaching-learning spaces. For higher education students, including graduate students, engaging in academic writing tasks is a challenge, and its performance plays a crucial role in their formative and professional development (Chen et al., 2021; Conijn *et al*., 2020). Therefore, the specialized literature asserts that academic writing is a skill requiring scaffolding (Errázuriz, 2017; Marinkovich and Poblete, 2014), and utilizing feedback as a strategy is of paramount importance (Cuevas-Solar and Arancibia, 2020).

[1] This research is being developed with the support of the Applied Research and Innovation Department of the Duoc UC Professional Institute, through the FACE02 project.

DOI: https://doi.org/10.15443/codes2019

Given the rise in the development of computer tools, it is encouraging to use them strategically to enhance the accomplishment of educational objectives (Salinas, 2008). Thus, automated text revision can be extremely helpful for the development of writing skills (Link *et al.*, 2020).

In this framework, the purpose of this research is to evaluate and compare the type of feedback for the development of academic writing that automatic feedback tools, such as ArText, Estilector, and PEUMO, and an artificial intelligence (ChatGPT 3.5), are able to produce. Specifically, the type of feedback they deliver is identified based on the categories proposed by Alvarez *et al*. (2011) and Guasch *et al*. (2013).

## 2 Theoretical Framework

In the educational field, *feedback* is a strategy aimed mainly at the student. Through it, the student is provided with the necessary information so that they can recognize their successes and understand the eventual mistakes made during a process, enabling them to correct those mistakes in order to achieve the expected learning (Silva Cruz, 2013; Boud and Molloy, 2015; Canabal and Margalef, 2017; Trejo, 2021). In academic writing (Carlino, 2005; Hyland, 2008), which also functions as a means of accrediting learning, feedback is key (Cuevas-Solar and Arancibia, 2020). Therefore, in recent years, several investigations have studied this phenomenon linked to writing processes when provided by human tutors (Hartshorn and Evans, 2015; Huisman et al., 2018; Arancibia et al., 2019; Venegas et al., 2022; Sologuren and Morgado, 2023). Through the strategic implementation of this practice, teachers guide and foster a literate culture within a specific disciplinary field (Errázuriz, 2017), not only to reproduce knowledge but also to transform it (Scardamalia and Bereiter, 1992).

The evolution of natural language processing techniques (Shermis, 2020) and of the information industry, in general, has led to the creation of various technological tools that can become powerful allies to carry out processes of accompaniment and providing expedient feedback during writing (Strobl *et al*., 2019; Lillo *et al*., 2023). In this field, academic discursive genres, due to their generally stable and prototypical characteristics (Swales, 1990; Camps and Castelló, 2013), have been ad hoc objects for evaluation. For Spanish, some of the most significant cases of these tools are: ArText[2] (Da Cunha et al., 2017), Estilector[3] (Nazar and Renau, 2023) and PEUMO[4] (Venegas and Cerda, 2022).

## 3 Methods

The method involves a deductive analysis of the manual application of feedback categories based on the types established by Álvarez *et al.* (2011) and specified by Guasch

[2] Available at http://sistema-artext.com/
[3] Available at http://www.estilector.com/
[4] Available at http://www.redilegra.com/peumo/

DOI: https://doi.org/10.15443/codes2019

*et al.* (2013). Considering the initial testing of the method, it was also deemed appropriate to use the corrective + suggestive *feedback* category proposed by Venegas *et al.* (2022). **Table 1** shows the specification of these categories.

**Table 1.** Specification of the 5 types of *feedback* used for the analysis.

| ***Feedback* category** | **Definition** |
|---|---|
| *Corrective* | Comments on the adequacy of meeting the task's requirements. |
| *Epistemic* | Requests for explanations and/or clarifications in a critical manner regarding an aspect of the task. |
| *Suggestive* | Includes tips on how to proceed, inviting exploration, expansion, or improvement of idea expression. |
| *Corrective + Suggestive* | Combines comments and advice as previously defined. |
| *Epistemic + Suggestive* | Entails requests for explanations and advice on how to resolve issues. |

The materials used for the research are as follows: 1) A corpus composed of ten[5] introductions from Degree Portfolios[6] of last semester students of the Duoc UC Professional Institute 2) Four computational tools that are plausible for the automatic feedback of academic writing, namely: ArText (Da Cunha *et al.*, 2017), Estilector (Nazar and Renau, 2023), PEUMO (Venegas and Cerda, 2022) and the Artificial Intelligence ChatGPT 3.5.

## 4 Results

The annotators who conducted the analysis were four professionals specialized in writing didactics. After evaluating all types of feedback in a text (26 cases), a Fleiss Kappa of 0.42 was obtained, with a 95% confidence interval. This index categorizes these preliminary results as having moderate annotator agreement.

The initial findings of the study (**Table 2 and Fig. 1**), based on the analysis of 10 texts (representing 33% of the total sample), are presented below. To enhance visualization, the percentages corresponding to the mean of each labeled feedback type have been depicted.

[5] This number corresponds to 33% of the total number of texts which will be analyzed by the end of the project.

[6] The discursive genre, which is situated in the curriculum of the Instituto Profesional Duoc UC, is integrated into a course of the same name, taken during the final stage of training. This course represents the second phase of a broader process that begins upon entering the program. In the initial stage, students engage in key subjects aim at developing essential competencies, while reflecting on their progress, strengths, and weaknesses. Based on this and to the characteristics proposed by Venegas *et al.* (2016), it can be attributed to the framework of the macro-genre known as Final Degree Project.

DOI: https://doi.org/10.15443/codes2019

**Table 2.** Percentage of *feedback* types by computational tool.

| *Computational tool* | *Corrective* | *Epistemic* | *Suggestive* | *Corrective + Suggestive* | *Epistemic + Suggestive* |
|---|---|---|---|---|---|
| *ArText* | 11,1% | 0,0% | 8,6% | 80,2% | 0,0% |
| *Estilector* | 13,8% | 0,0% | 6,9% | 72,4% | 6,9% |
| *PEUMO* | 36,2% | 0,0% | 6,9% | 56,9% | 0,0% |
| *ChatGPT 3.5* | 17,2% | 2,3% | 5,7% | 70,1% | 4,6% |

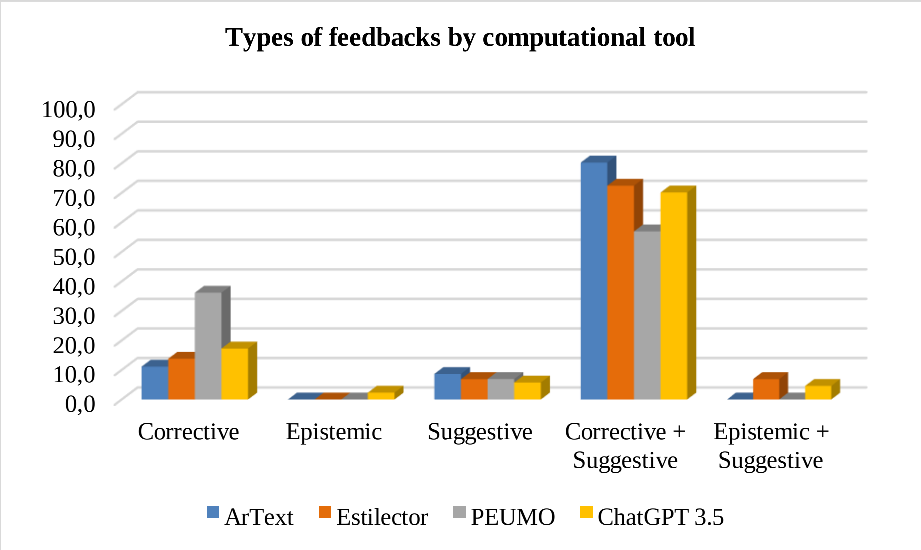


**Fig. 1.** Visual representation of the data expressed in **Table 2**.

## 5 Preliminary conclusions and projections

Based on the data we have collected thus far; we have identified some relevant findings that could be retained and/or potentially highlighted as the analysis phase concludes.

a) An expansion of the categories presented by Guasch *et al*. (2013) has been observed. The insight shared by Venegas *et al*. (2022), integrated in this study, has proven valuable for understanding the *feedback* phenomenon.
b) It should be considered that these tools have the capacity to provide feedforward-type feedback (not just feedback). This type of feedback is linked to guiding and providing motivational support for future tasks, i.e., in a constructive-projective sense (Canabal and Margalef, 2017). Qualitative analysis primarly demonstrates this typology in relation to corrective-type *feedback*.
c) In quantitative terms, our projections indicate a prevailing tendency for the automatic *feedback* tools under analysis to predominantly generate corrective +

DOI: https://doi.org/10.15443/codes2019

suggestive *feedback*. Furthermore, we anticipate that, in comparative terms, there will be no significant variation in results when compared to those generated by AI. This aspect warrants special attention, as the specific writing *feedback* tools (ArText, Estilector, and PEUMO) operate based on predefined instructions that users cannot modify. In contrast, ChatGPT, allows users to generate and specify the PROMPT.

d) It is projected that none of the four analyzed tools, including AI, is capable of providing epistemic *feedback*. As a result, it appears that this role would continue to be solely within the realm of a human tutor specialized in the subject of the text.

## References

Álvarez, I., Espasa, A., and Guasch, T. (2011). The value of feedback in improving collaborative writing assignments in an online learning environment. *Studies in Higher Education*, 37, 387– 400.

Arancibia, B., Tapia-Ladino, M., and Correa, R. (2019). La retroalimentación durante el proceso de escritura de la tesis en carreras de pedagogía: Descripción de los comentarios escritos de los profesores guías. *Revista signos*, 52(100), 242-264.

Boud, D. and Molloy, E. (2015). *El feedback en educación superior y profesional: comprenderlo y hacerlo bien*. Narcea Ediciones.

Camps, A. and Castelló, M. (2013). La escritura académica en la Universidad. *REDU: Revista de docencia Universitaria*, *11*(1), 17.

Canabal, C. and Margalef, L. (2017). La retroalimentación: la clave para una evaluación orientada al aprendizaje. Profesorado. *Revista de currículum y formación del profesorado*. 21(2), 149-170.

Carlino, P. (2005). *Escribir, leer y aprender en la universidad: una introducción a la alfabetización académica*. Buenos Aires: Fondo de Cultura Económica.

Chen, H. J. H., Lai, S. L., Lee, K. Y., and Yang, C. T. Y. (2023). Developing and evaluating an academic collocations and phrases search engine for academic writers. *Computer Assisted Language Learning*, 36(4), 641-668.

Conijn, R., Martinez-Maldonado, R., Knight, S., Buckingham Shum, S., Van Waes, L., and van Zaanen, M. (2022). How to provide automated feedback on the writing process? A participatory approach to design writing analytics tools. *Computer Assisted Language Learning*, 35(8), 1838-1868.

DOI: https://doi.org/10.15443/codes2019

Cuevas-Solar, D. and Arancibia, B. (2020). Percepciones y expectativas de docentes de ingeniería y educación en torno a la retroalimentación en tareas de escritura. *Formación universitaria*, 13 (4), 31-44.

Da Cunha, I., Montané, M. A. and Hysa, L. (2017). The arText prototype: An automatic system for writing specialized texts. In Martins A, Peñas A, editors. EACL 2017. 15th *Conference of the European Chapter of the Association for Computational Linguistics. Proceedings of the Software Demonstrations*; 2017 Apr 3-7; Valencia, Spain. Stroudsburg (PA): ACL; 2017. p. 57-60. ACL (Association for Computational Linguistics).

Errázuriz, M. C. (2017). Teorías implícitas sobre la escritura académica en estudiantes de programas de formación inicial docente: ¿inciden en el desempeño escrito? *Signo y pensamiento*, 36 (71), 36-52.

Guasch, T., Espasa, A., Alvarez, I. M., and Kirschner, P. A. (2013). Effects of feedback on collaborative writing in an online learning environment. *Distance education*, 34 (3), 324-338.

Hartshorn, K. J., and Evans, N. W. (2015). The effects of dynamic written corrective feedback: A 30-week study. *Journal of response to writing*, 1(2), 2.

Hyland, K. (2008). Genre and academic writing in the disciplines. *Language Teaching*, 41(4), 543-562.

Huisman, B., Saab, N., Van Driel, J. and Van Den Broek, P. (2018). Peer feedback on academic writing: undergraduate students' peer feedback role, peer feedback perceptions and essay performance. *Assessment & Evaluation in Higher Education*, 43(6), 955-968.

Lillo-Fuentes, F., Venegas, R., and Lobos, I. (2023). Evaluación automatizada y semi-automatizada de la calidad de textos escritos: una revisión sistemática. *Perspectiva Educacional*, 62(2), 5-36.

Link, S., Mehrzad, M., and Rahimi, M. (2020). Impact of automated writing evaluation on teacher feedback, student revision, and writing improvement. *Computer Assisted Language Learning*, 35(4), 605-634.

Marinkovich, J. and Poblete, C. (2014). Alfabetización en escritura académica en Biología: propósitos comunicativos y niveles de alfabetización. *Onomázein*, 30, 269-285.

Nazar, R. and Renau, I. (2023). Estilector: Un sistema de evaluación automática de la escritura académica en castellano. *Perspectiva Educacional. Formación de profesores*, 62(2), 37-59.

DOI: https://doi.org/10.15443/codes2019

Parodi, G., Ibáñez, R. and Venegas, R. (2010). Discourse genres in PUCV-2006 Corpus of Academic and Professional Spanish: Criteria, definitions and examples. En G. Parodi (ed.), *Discourse genres in Spanish: Academic and professional connections* (pp. 39-68). Amsterdam: Benjamins.

Salinas, J. (2008). Innovación educativa y uso de las TIC. In *Innovación educativa y uso de las TIC* (pp. 15-26). Universidad Internacional de Andalucía.

Scardamalia, M., and Bereiter, C. (1992). Dos modelos explicativos de los procesos de composición escrita. *Infancia y aprendizaje*, 15 (58), 43-64.

Shermis, M. D. (2020). International Applications of Automated Scoring. In *Handbook of Automated Scoring* (pp. 113-132). Chapman and Hall/CRC.

Silva Cruz, M. I. (2013). La retroalimentación en la corrección de la escritura: Corrección y autocorrección en el aprendizaje de alumnos norteamericanos. *Revista Nebrija de Lingüística Aplicada*, 7 (3).

Sologuren, E., and Morgado, P. (2023). Prácticas de retroalimentación para la producción del género de formación "Informe de Proyecto" en Ingeniería y Ciencias: explorando el aula universitaria. *Perspectiva Educacional*, 62(2), 114-139

Strobl, C., Ailhaud, E., Benetos, K., Devitt, A., Kruse, O., Proske, A. and Rapp, C. (2019). Digital support for academic writing: A review of technologies and pedagogies, *Computers & Education*, 131, 33-48

Swales, J. (1990). *Genre analysis. English in academic and research settings*. Cambridge University Press.

Trejo, E. (2021). La retroalimentación oral o escrita para mejorar la producción escrita en la universidad. *Educación*, 27 (1), 79-83.

Venegas, R., Zamora, S., and Galdames, A. (2016). Hacia un modelo retórico-discursivo del macrogénero Trabajo Final de Grado en Licenciatura. *Revista signos*, *49*, 247-279.

Venegas, R. and Cerda, C. (2022). Herramienta computacional de apoyo a la escritura del Informe técnico para estudiantes de ingeniería civil. XXXIV Congreso Chileno de Educación en Ingeniería 2022, Santiago de Chile.

Venegas, R., Ahumada, J., and Sologuren, E. (2022). Tipos y formas de retroalimentación en informes de laboratorio en ingeniería eléctrica: aproximación a la producción de un género de formación. *CÍRCULO de Lingüística Aplicada a la Comunicación*, 89.