Didaktik Deutsch

Cerstin Mahlow

Writing versus automated text production by generative AI: Distinctions, disruptions, and the need for new models

1 Introduction

In written societies, literacy (reading and writing) is essential for participation and has always been intertwined with technology. In the 1990s, the Internet moved reading and writing into the digital space. Now, large language models (LLMs) and generative AI (GenAI) are transforming literacy once more.

AI-based language technology offers unprecedented opportunities for inclusion and writing support such as automatic plain language translation (Ebling et al., 2022) and written language acquisition (Mahlow, 2023a). Today's computing power, mature natural language processing (NLP) technology, and LLMs make it feasible to realize innovative ideas for adaptive human-centered writing support (Mahlow, 2023b) and adaptive writing tools (Mahlow & Piotrowski, 2009). However, we lack an understanding of *how* GenAI fundamentally alters writing processes. This paper first explicates the context and defines text generation and automated text production in contrast to writing. This leads to the proposal of rigorous revisions of writing models as part of an extensive research agenda to reflect the integration of GenAI and its cognitive impact.

2 Context: The bigger picture

With the appearance of ChatGPT in November 2022, the general public was confronted with impressive developments in the field of language technology and artificial intelligence. Additionally, various professional fields are being called into question.

The embedding of GPT3.5 in a simple chat interface has led to astonished as well as enthusiastic reactions. The sometimes euphoric assessments that anyone can now create professional-looking texts by a simple request to a chatbot have shaken professional fields such as communication, technical writing, copywriting, marketing, and translation: If these automatically produced texts, as Mahlow and Dale (2014) call them, are as good as those of professional translators and copywriters, what does this mean for the entire industry? And downstream, the question: What does such an upheaval in fields of practice mean for corresponding courses of study and further education?

Didaktik Deutsch
Halbjahresschrift für die Didaktik der deutschen Sprache und Literatur
Special Issue (2026) – Writing with AI. S. 19–28
DOI: 10.21248/dideu.956

There was a similar upheaval in the field of translation and interpreting a few years before: the power of automatic machine translation based on LLMs created by neural learning (Bahdanau et al., 2014) and its general availability in the mid-2010s in online services such as Google Translate (Wu et al., 2016) and DeepL posed enormous challenges for the industry itself (cf. Bouillon et al., 2018) as well as for training concepts and institutions (cf. Cotelli Kureth et al., 2023). In retrospect, the adaptation to this has been successful—well-trained professional translators and interpreters continue to be used for many areas.

Both chatbots and language models have been research topics in human–machine communication and computational linguistics for quite a long time. Chatbots based on GenAI are not restricted in terms of language—both for interaction and for the desired text—and text type. However, upon closer examination, it turns out that both the interaction with such chatbots and the quality of the texts produced depend on the training material for the language models, and this is mostly not disclosed. In addition, users do not interact directly with the language models, but by means of a chat interface that filters and expands both input and output.

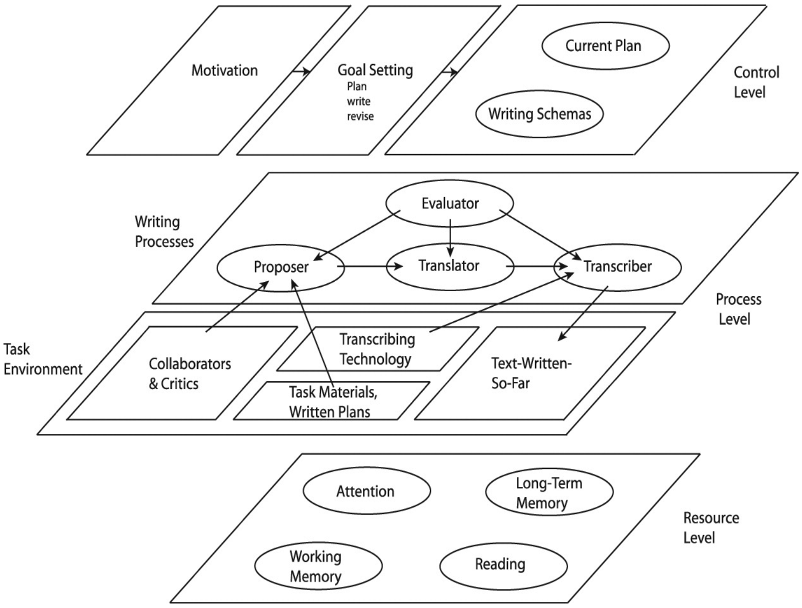
Since ChatGPT's release in late 2022, we have witnessed the impact of GenAI on language professions. In fields such as communication, copywriting, and translation, GenAI challenges established roles and processes. Mastering these tools and using them successfully requires more than "prompt engineering"—which is a misnomer because no proper engineering is involved. It demands evaluating the quality of AI-produced texts and using them responsibly in professional contexts. GenAI for text production is also reshaping how we teach and practice writing (cf. Anson et al., 2025).

Current studies on GenAI in writing focus on stand-alone tools (see, e.g., Bedington et al., 2024; Cummings et al., 2024; Tarchi et al., 2024), but the trend is moving toward integrating GenAI directly into writing tools. To make best use of it, we need to understand how automated text production by GenAI works. If we are to help writers interact with GenAI efficiently and effectively, the writing research community must understand what GenAI can and cannot do. As I argued in my SIG Writing 2024 keynote (*On the road to language-aware writing support—are we there yet with large language models?*), the scientific community currently lacks a comprehensive writing model to account for GenAI.

I am specifically interested in understanding writing on a linguistic level (Mahlow et al., 2024) and work on respective models (Ulasik et al., 2025) based on keystroke-logging experiments. Referring to Hayes' comprehensive writing model (Hayes, 2012; see Figure 1), our studies focus on the interplay of Transcriber (process level), Transcribing Technology and Text-Written-So-Far (task environment) for drafting and revising.

Figure 1

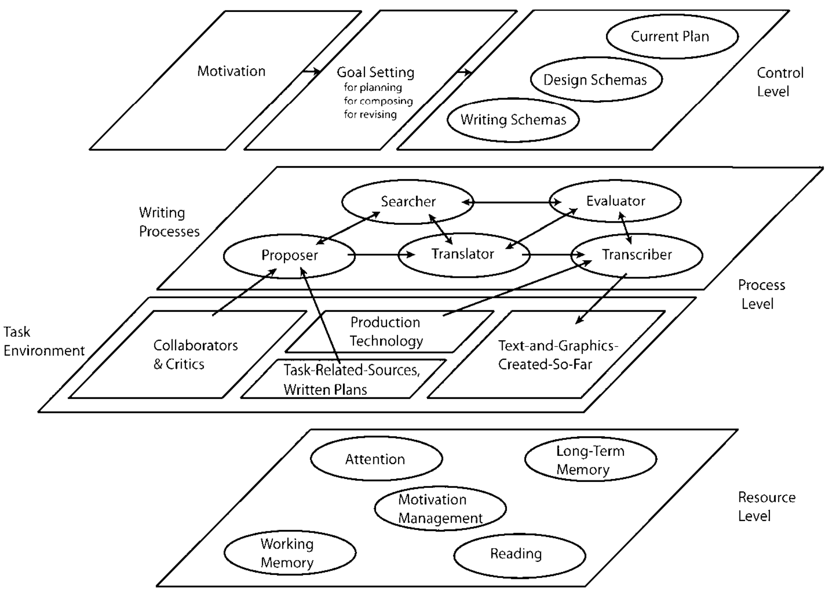
Hayes' 2012 Model of the Writing Process (Hayes, 2012)



Writing models aim to capture how people actually write. However, these models sometimes fail (Bazerman, 2018), and need to be extended or adjusted. For example, Leijten et al. (2014) extend Hayes' model to account for skilled professional communication (see Figure 2), explicitly including collaboration and nontextual creation resulting in adjustments on all levels (Schriver, 2013). As GenAI changes the way people write, clearly writing models need revisions.

Figure 2

Extended Model by Leijten et al. (2015) to Cover Professional Communication



Additionally, writing models should be implementable as running programs (Alamargot & Chanquoy, 2001; Hayes, 2012) following the practice of creating running programs to simulate human actions in cognitive science (Newell & Simon, 1956). They are considered to be an implementation of a theory (Weizenbaum, 1976) that serve as a basis for designing tools to support writing (Cookson, 1989). So far, we, as the writing research community, have not succeeded in this matter—probably because we did not tackle this task seriously, except for a few attempts to implement some aspects of children writing in Python by Hayes (2012).

3 Automated text production versus natural language generation versus writing

To understand the impact on writing, we need to answer the question: When LLMs produce text, what is that, really? The output of applications using LLM is often called "generated text," using a term that already has a specific meaning in the field of natural language generation (NLG). NLG is the production of "understandable texts in . . . human languages from some underlying non-linguistic representation of information" (Reiter & Dale, 1997, p. 57) and has been an active research field for several decades. In analogy to text-to-speech, it has also been named data-to-text (Schneider et al., 2022).

Data (e.g., measure points, facts in knowledge bases, entire databases), as nonlinguistic representation of information, is the explicit context of the text to be generated and the most important aspect of NLG systems. This context is made available in structured form to the machine that generates the text. Additionally, all information about intended audience, genre, text length, and so forth has to be made explicit as well, and is used as features and parameters for generation. Usually, these systems involve human curation or are (at least partially) based on human-generated rules. Dale (2020) gives an overview of the (commercial) state of the art on NLG; Schneider et al. (2022) describe categories of NLG systems. They emphasize that:

> data-to-text systems in real-world applications still require such a share of human configuration and control and the creative contribution share of the software . . . is still so limited that it would not be adequate to claim creative autonomy of the software in the process. (p. 1)

Current language technology such as NLG is thus not an autonomous creative agent taking part in the writing process. There is no *interaction* between a human writer and a text-producing machine, only very sophisticated *interactivity* (cf. Rafaeli, 1988).

Language technology is used for writing support in settings of *automated text production* as defined by Mahlow and Dale (2014) with the deliberate emphasis that, in these cases, it is not the author that is the writer, but the machine. They see NLG as one aspect of automated text production and also mention summarization or machine translation: A new text is produced without human intervention, based on existing text or explicit prompts.

In a revision of the work by Mahlow and Dale (2014), I suggest to distinguish *text generation* from *automated text production*:

1. *Text generation* covers NLG. It is characterized by relying on nonlinguistic representations of information and involving some kind of text planning. Planning concerns the text as a whole—length, main information, structure, and so forth—as well as single sentences.
2. *Automated text production* is the output of current LLMs as fast continuous predictive texting—known from input-support on mobile phones (Ganslandt et al., 2009)—by design. No facts and information determine the next words or sentences, but only available co-texts of already existing words and sentences—when writing from left to right, there is always only

left co-text. Note that what computer science and NLP call "context" as used in "size of context window" to describe the power of an LLM is, in linguistics, called "co-text," whereas "context" refers to everything outside the text.

Such systems are operated by humans through communication using unrestricted natural language. There is no planning of either the text as a whole or individual sentences; and, more importantly, no revision and editing take place. The text is produced as a plausible continuation of already existing text. Hence the similarity to predictive texting. The resulting text is correct from a linguistic point of view: it does not contain spelling and grammar issues; it is most probably coherent and consistent on the sentence level. But it is plausible and acceptable only when focusing on the *language* produced. Automated text production is linear or actually *incremental* both in time *and* in space: One token after the other is added to the edge of the text produced so far (TPSF).

Writing, in contrast, can be characterized as involving planning—the degree can of course vary—and more importantly: Writing is linear in time, but never linear in space. Writers can and do go back to text already written (TPSF) at any point in time and delete or add something; they reorder text parts for various reasons—style, change in plans, and so forth. They consider left *and* right co-text as well as context including the writing task and their own planning. None of these movements will be visible in the final product.

Dale and Viethen (2021) provide an overview on writing assistance based on state-of-the-art NLP resources (i.e., language models) and approaches. In 2021, GPT-3 was already available and had been incorporated into various tools aimed at supporting writers by co-authoring and not only (copy-)editing. These applications addressed specific genres such as blog posts and poetry, as well as specific writing tasks such as expanding, rewriting, and shortening texts (Dale & Viethen, 2021). However, they were not used widely and did not trigger the same discussions that we see now.

The more powerful LLMs get, the more users forget that texts automatically produced by any application using these resources are just plausible extensions of existing co-text. These co-texts are either existing (parts of) texts, which are then extended, or prompts the system seems to "react" to: "GPT-3 is still very capable of generating nonsense, but on the whole it's more plausible nonsense; and with appropriate fine tuning and prompting, the texts it generates can be eerily convincing" (Dale & Viethen, 2021, p. 516).

All information that seems to be included in the text is merely due to frequent co-occurrences of words and thus not trustworthy (cf. Kalai et al., 2025). No references to any context (i.e., the world outside the text) can be made; no conclusions on underlying knowledge, understanding, or intention of an assumed author can be drawn. Depending on the genre the LLM is asked to produce, a text may contain what looks like facts (e.g., dates, places, or even correctly formatted bibliographical references). But again, these are only *plausible*, they are not true; they could, but most often do not, exist. The LLM just produces sequences of words that follow general patterns for bibliographical entries. While references produced by an LLM are thus most probably nonexistent, one can very confidently use them to check whether the *format* of a list of bibliography entries adheres to a certain citation style.

These systems are not creative: They do not invent anything, because they have no agency. They just react to any input—be it a prompt from a human or previously produced text. All creativity, all surprisal is only in the mind of human readers interpreting these texts, ignoring authorship, and not being aware of the circumstances (i.e., the process) of their production.

4 A research agenda

Writing research as a scientific community needs to closely observe and carefully analyze current writing and text production practices. Writing models were always intended to explain what happens during writing. With new tools and new affordances come new practices currently not covered by existing models. As a field, we need to work on respective topics and most probably need to develop new approaches.

4.1 Research topics

I pose four research topics that need to be addressed through interdisciplinary research:

1. Seeing GenAI as co-author, as Armitage (2024) and Kleebayoon and Wiwanitkit (2023) do, requires the extension of collaborative writing models to include nonhuman authors.
2. GenAI intervenes at all stages of the writing process and on all levels of existing models. No single generic GenAI writing tool exists, but an ever-growing number of GenAI-based tools tailored to specific uses (or GenAI-based features integrated into existing tools for specific purposes such as Grammarly or Antidote) are being developed and used that allow elements in writing models to be linked to distinct GenAI features.
3. GenAI-based automated text production as part of writing fundamentally disrupts writing as a practice as well as a concept, requiring new models to account for its role in creative tasks and cognitive load.
4. The adequate and deliberate use of GenAI shifts focus to higher-level tasks such as planning. Which would be a good thing, if true.

The revision of writing models will generate further research questions like those addressing Research Topic 4 for psycholinguistic experiments. First observations suggest that GenAI could be used as Transcriber. In Hayes' (2012) model, Transcription is the actual production of visible text by handwriting or typing, and it involves spelling (Berninger & Winn, 2006). Higher-level activities such as planning require a significant amount of cognitive capacity. The more writers automate lower-level tasks (e.g., master touch-typing), the more they can focus on planning, and so forth (Hayes & Chenoweth, 2006; Kellogg, 1999; Olive, 2022; Olive et al., 2009; Quinlan et al., 2012), because limited working memory must be distributed to different tasks (Olive, 2014).

4.2 Advance methodology

Writing research always incorporated methods and approaches from different fields and is truly interdisciplinary. To address the research topics presented above, writing research needs to look at current developments in NLP, human–computer interaction, and the neurosciences (cf. Zock, 2020). First studies looking at not only the efficacy of integrating GenAI into writing courses by triangulation of product and process data but also research methods are already under way (e.g., Schnatz & Bieri, 2025).

For Research Topic 4 specifically, there is a need to adapt methods from Bouriga and Olive (2021) and Liu et al. (2024) for controlled experiments focusing on producing running text from outlines by calling specific GenAI features in editors with integrated GenAI features. Established methodologies are insufficient. A new approach is needed to capture how GenAI reshapes cognitive load and higher-order tasks such as planning. Collaboration with psycholinguistics is needed to adapt double and triple task paradigms (cf. Olive et al., 2002). GenAI's integration into writing involves dynamic and unpredictable interactions, emphasizing the need to develop experimental protocols that account for these nuances, including how GenAI influences the distribution of cognitive resources during the writing process.

4.3 What to expect

The proposed research ideas and topics add significant value to writing research and writing instruction as well as to society at large. By exploring how GenAI can enhance cognitive aspects of writing, they address key issues at the intersection of AI, writing processes, and education.

On a societal level, this research agenda addresses the pressing issue of (digital) literacy in a world soon to be imbued with AI—one might even argue that this has already happened. Writing remains an essential skill involving cognitive processes, but it is undergoing radical shifts due to new GenAI-based text production tools and the integration of GenAI into existing writing technology. This research agenda will provide insights into how these shifts can be harnessed. It will directly inform teaching practices by proposing improved methods for teaching writing (both learning-to-write and writing-to-learn).

GenAI-based tools or GenAI-driven features in writing tools promise to improve writing efficiency and efficacy: There is a clear need to validate and operationalize these claims by transferring them into practice. Methodological development of AI-assisted writing models will contribute to writing research as a scientific field and to frameworks for digital education that transform how writing is taught in universities and professional settings.

5 Conclusion

The integration of generative AI (GenAI) into writing represents a paradigm shift that calls for a reevaluation of writing models, pedagogical approaches, and digital literacy. This paper tries to explicate the roles of language technology in text production and proposes a research agenda addressing this shift through empirical studies and interdisciplinary research to develop new writing models that account for GenAI as collaborator and cognitive scaffold.

References

Alamargot, D., & Chanquoy, L. (2001). *Through the models of writing: With commentaries by Ronald T. Kellogg & John R. Hayes* (Vol. 9). Springer. http://www.worldcat.org/isbn/0792371593

Anson, C. M., Delorme Benites, A., Ganobcsik-Williams, L., Mahlow, C., & McKee, H. A. (2025). Reflections on writing and generative AI: A symposium. *Journal of Academic Writing, 15*(S2), 1–14. https://doi.org/10.18552/joaw.v15iS2.1121

Armitage, R. (2024). Generative AI in medical writing: Co-author or tool? *British Journal of General Practice, 74*(740), 126–127. https://doi.org/10.3399/bjgp24X736605

Bahdanau, D., Cho, K., & Bengio, Y. (2014). Neural machine translation by jointly learning to align and translate. *arXiv*. https://doi.org/10.48550/arXiv.1409.0473

Bazerman, C. (2018). What does a model model? And for whom? *Educational Psychologist, 53*(4), 301–318. https://doi.org/10.1080/00461520.2018.1496022

Bedington, A., Halcomb, E. F., McKee, H. A., Sargent, T., & Smith, A. (2024). Writing with generative AI and human–machine teaming: Insights and recommendations from faculty and students. *Computers and Composition, 71*, Article 102833. https://doi.org/10.1016/j.compcom.2024.102833

Berninger, V. W., & Winn, W. D. (2006). Implications of advancements in brain research and technology for writing development, writing instruction, and educational evolution. In *Handbook of writing research* (pp. 96–114). The Guilford Press.

Bouillon, P., Girletti, S., Estrella, P., Mutal, J., Bellodi, M., & Bircher, B. (2018). Integrating MT at Swiss Post's language service: Preliminary results. *Proceedings of the 21st Annual Conference of the European Association for Machine Translation* (pp. 281–286). http://hdl.handle.net/10045/76086

Bouriga, S., & Olive, T. (2021). Is typewriting more resources-demanding than handwriting in undergraduate students? *Reading and Writing, 34*(9), 2227–2255. https://doi.org/10.1007/s11145-021-10137-6

Cookson, S. (1989). Designing computational writing tools within a linguistic model of the writing process. In N. Williams & P. O. Holt (Eds.), *Computers and writing: Models and tools* (pp. 17–21). Intellect.

Cotelli Kureth, S., Delormes Benites, A., Haller, M., Noghrechi, H., & Steele, E. (2023). "I looked it up in DeepL": Machine translation and digital tools in the language classroom. In *Human translation and natural language processing towards a new consensus?* Fondazione Università Ca' Foscari. https://doi.org/10.30687/978-88-6969-762-3/006

Cummings, R. E., Monroe, S. M., & Watkins, M. (2024). Generative AI in first-year writing: An early analysis of affordances, limitations, and a framework for the future. *Computers and Composition, 71*, Article 102827. https://doi.org/10.1016/j.compcom.2024.102827

Dale, R. (2020). Natural language generation: The commercial state of the art in 2020. *Natural Language Engineering, 26*(4), 481–487. https://doi.org/10.1017/S135132492000025X

Dale, R., & Viethen, J. (2021). The automated writing assistance landscape in 2021. *Natural Language Engineering, 27*(4), 511–518. https://doi.org/10.1017/S1351324921000164

Ebling, S., Battisti, A., Kostrzewa, M., Pfütze, D., Rios, A., Säuberli, A., & Spring, N. (2022). Automatic text simplification for German. *Frontiers in Communication, 7*, Article 706718. https://doi.org/10.3389/fcomm.2022.706718

Ganslandt, S., Jörwall, J., & Nugues, P. (2009). Predictive text entry using syntax and semantics. *Proceedings of the 11th International Conference on Parsing Technologies*, 37–48.

Hayes, J. R. (2012). Modeling and remodeling writing. *Written Communication, 29*(3), 369–388. https://doi.org/10.1177/0741088312451260

Hayes, J. R., & Chenoweth, N. A. (2006). Is working memory involved in the transcribing and editing of texts? *Written Communication, 23*(2), 135–149. https://doi.org/10.1177/0741088306286283

Kalai, A. T., Nachum, O., Vempala, S. S., & Zhang, E. (2025). Why language models hallucinate. https://arxiv.org/abs/2509.04664

Kellogg, R. T. (1999). Components of working memory in text production. In M. Torrance & G. Jeffery (Eds.), *The cognitive demands of writing: Processing capacity and working memory effects in text production* (Vol. 3, pp. 42–61). Amsterdam University Press.

Kleebayoon, A., & Wiwanitkit, V. (2023). Use of ChatGPT as a co-author. *ESMO Open, 8*(4). https://doi.org/10.1016/j.esmoop.2023.101620

Leijten, M., Van Waes, L., Schriver, K., & Hayes, J. R. (2014). Writing in the workplace: Constructing documents using multiple digital sources. *Journal of Writing Research, 5*(3), 285–337. https://doi.org/10.17239/jowr-2014.05.03.3

Leijten, M., Van Waes, L., & Horenbeeck, E. V. (2015). Analyzing writing process data: A linguistic perspective. In G. Cislaru (Ed.), *Writing(s) at the crossroads: The process/product interface* (pp. 277–302). John Benjamins Publishing Company. https://doi.org/10.1075/z.194.14lei

Liu, M., Zhang, L. J., & Biebricher, C. (2024). Investigating students' cognitive processes in generative AI-assisted digital multimodal composing and traditional writing. *Computers & Education, 211*, Article 104977. https://doi.org/10.1016/j.compedu.2023.104977

Mahlow, C. (2023a). Large language models and artificial intelligence as tools for teaching and learning writing. *Osnabrücker Beiträge zur Sprachtheorie, 101*, 175–196. https://doi.org/10.17192/OBST.2023.101.8607

Mahlow, C. (2023b). Writing tools: Looking back to look ahead. https://arxiv.org/abs/2303.17894

Mahlow, C., & Dale, R. (2014). Production media: Writing as using tools in media convergent environments. In E.-M. Jakobs & D. Perrin (Eds.), *Handbook of writing and text production* (Vol. 10, pp. 209–230). De Gruyter Mouton.

Mahlow, C., & Piotrowski, M. (2009). LingURed: Language-aware editing functions based on NLP resources. *Proceedings of the International Multiconference on Computer Science and Information Technology, 4*, 243–250. https://annals-csis.org/proceedings/2009/PTI/pliks/101.pdf

Mahlow, C., Ulasik, M. A., & Tuggener, D. (2024). Extraction of transforming sequences and sentence histories from writing process data: A first step towards linguistic modeling of writing. *Reading and Writing, 37*, 443–482. https://doi.org/10.1007/s11145-021-10234-6

Newell, A., & Simon, H. (1956). The logic theory machine: A complex information processing system. *IRE Transactions on Information Theory, 2*(3), 61–79. https://doi.org/10.1109/TIT.1956.1056797

Olive, T. (2014). Toward a parallel and cascading model of the writing system: A review of research on writing processes coordination. *Journal of Writing Research, 6*(2), 173–194. https://doi.org/10.17239/jowr-2014.06.02.4

Olive, T. (2022). How do novice and skilled writers engage working memory? In J. W. Schwieter & J. Cheng (Eds.), *The Cambridge handbook of working memory and language* (pp. 504–526). Cambridge University Press. https://doi.org/10.1017/9781108955638.028

Olive, T., Alves, R. A., & Castro, S. L. (2009). Cognitive processes in writing during pause and execution periods. *European Journal of Cognitive Psychology, 21*(5), 758–785. https://doi.org/10.1080/09541440802079850

Olive, T., Kellogg, R. T., & Piolat, A. (2002). The triple task technique for studying the process of writing. In T. Olive & C. M. Levy (Eds.), *Contemporary tools and techniques for studying writing* (Vol. 10, pp. 31–59). Kluwer.

Quinlan, T., Loncke, M., Leijten, M., & Van Waes, L. (2012). Coordinating the cognitive processes of writing. *Written Communication, 29*(3), 345–368. https://doi.org/10.1177/0741088312451112

Rafaeli, S. (1988). Interactivity: From new media to communication. *Advancing Communication Science: Sage Annual Review of Communication Research, 16*, 110–134.

Reiter, E., & Dale, R. (1997). Building applied natural language generation systems. *Natural Language Engineering*, *3*(1), 57–87. https://doi.org/10.1017/S1351324997001502

Schnatz, N. I., & Bieri, A. (2025). Refining an AI-integrated scientific writing course for engineers: Insights from a design-based research approach. *EDULEARN25 Proceedings*, 2394–2406. https://doi.org/10.21125/edulearn.2025.0663

Schneider, A., Madsack, A., Heininger, J., Chen, C.-Y., & Weißgraeber, R. (2022). Data-to-text systems as writing environment. *Proceedings of the First Workshop on Intelligent and Interactive Writing Assistants (In2Writing 2022)*, 1–10. https://doi.org/10.18653/v1/2022.in2writing-1.1

Schriver, K. (2013). What do technical communicators need to know about information design? In J. Johnson-Eilola & S. Selber (Eds.), *Solving problems in technical communication* (pp. 386–427). University of Chicago Press.

Tarchi, C., Zappoli, A., Casado Ledesma, L., & Brante, E. W. (2024). The use of ChatGPT in source-based writing tasks. *International Journal of Artificial Intelligence in Education, 35*, 858–878. https://doi.org/10.1007/s40593-024-00413-1

Ulasik, M. A., Mahlow, C., & Piotrowski, M. (2025). Sentence-centric modeling of the writing process. *Journal of Writing Research, 16*(3), 463–498. https://doi.org/10.17239/jowr-2025.16.03.05

Weizenbaum, J. (1976). *Computer power and human reason: From judgment to calculation*. W. H. Freeman & Co.

Wu, Y., Schuster, M., Chen, Z., Le, Q. V., Norouzi, M., Macherey, W., Krikun, M., Cao, Y., Gao, Q., Macherey, K., Klingner, J., Shah, A., Johnson, M., Liu, X., Kaiser, Ł., Gouws, S., Kato, Y., Kudo, T., Kazawa, H., . . . Dean, J. (2016). Google's neural machine translation system: Bridging the gap between human and machine translation. *arXiv*. https://doi.org/10.48550/arXiv.1609.08144

Zock, M. (2020). AI at the crossroads of NLP and neurosciences. *Journal of Cognitive Science, 21*(1), 1–14.

Author's address:

Cerstin Mahlow, ZHAW Zurich University of Applied Sciences, School of Applied Linguistics, Theaterstraße 17a, 8401 Winterthur, Switzerland
cerstin.mahlow@zhaw.ch