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## Knowledge and Language Digitalization: The Case of Artificial Intelligence

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### Editorial. Knowledge and Digitalization of Communication Practices: The Case of Artificial Intelligence

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### The Model of Automated Knowledge Communication – Developing Specialized Communication Studies: An Outline

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### Integrating Artificial Intelligence in the Higher Education of Technical Writers and Translators

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### Maschinelle und menschliche Übersetzung im Vergleich am Beispiel des Entwurfs des ersten ungarischen Zivil- gesetzbuches (Deutsch – Slowakisch)

Peter Gergel, Ol'ga Wrede, Daša Munková & Lucia Benková

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### Do Translators Dream of Electric Brains?

Ricardo Muñoz Martín

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## Editorial.

# Knowledge and Digitalization of Communication Practices: The Case of Artificial Intelligence

*Helle Dam Jensen, Anne Schjoldager, Marian Flanagan,  
Tina Paulsen Christensen & Kristine Bundgaard*

In the introductory chapter to his book *Co-intelligence*, Ethan Mollick writes:

We have invented technologies, from axes to helicopters, that boost our physical capabilities; but we have never built a generally applicable technology that can boost intelligence. Now humans have access to a tool that can emulate how we think and write, acting as a co-intelligence to improve (or replace) our work. (Mollick 2024: xix–xx)

In other words, generative artificial intelligence (GAI) technology has a potential for replacing humans in some tasks, referred to as automation, and to complement humans in other tasks, referred to as augmentation (Lei/Kim 2024: 252). Lei/Kim (2024: 252) define augmentation as the integration of “technology into human workflows to enhance capabilities and productivity”. O’Brien (2023: 396) defines augmentation in a similar vein, but restricts the definition to technology that helps overcome the constraints of human cognition. It is this last definition which is relevant to this thematic issue, as the articles explore how technology can support human cognition by examining how knowledge is generated and transferred in text generation and translation.

The ability of technology to emulate human language and engage in dialogue with humans (Ferguson 2023: 4) facilitates practical applications useful for everyday tasks such as cooking, as demonstrated by chatbots that can automatically generate recipes (Feuerriegel et al. 2024: 1). The technology may also be used in professional communication for generating and reviewing texts, and for generating ideas. Interestingly, a comparative study on idea generation found that ideas created by humans were only slightly better than those generated by GAI (Haase/Hanel 2023). Other uses of GAI are automatically generated responses to customer inquiries in customer service (Ferguson 2023: 39), creation of personalised learning experiences (Mollick/Mollick 2024), and, in the area of teaching, automatic evaluations of students’ essays (Ferguson 2023: 45). Moreover, examples from translation include drafting, i. e. finding translation alternatives, and proofreading (see also Muñoz, this issue). All this shows that, with text generation standing “at the forefront of this digital revolution” – according to the Marketing provider AI Contentify – it is imperative to examine the impact of this new technology on human-computer interaction (HCI). Various researchers have pointed out that this development alters the nature of interaction between humans and machines. For instance, Markauskaite et al. (2022: 3 f.) point out that it reverberates with the relative distribution of “intelligence, la-

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bour and power between humans and machines". Along the same lines, Bubeck et al. (2023: 89, as cited by Krüger 2023: 3) argue that ChatGPT4's exceptional capabilities are set to redefine our views on the distribution of expertise between humans and machines.<sup>1</sup>

Given these technological advances, there is growing focus on how new artificial intelligence (AI) technologies impact and reshape competencies<sup>2</sup> required in society at large. Researchers have approached this challenge by developing frameworks that integrate necessary competencies into the broader concept of AI literacy (cf., for instance, Long/Magerko 2020 as well as Ng et al. 2021 and Laupichler et al. 2022, as cited by Krüger 2023). According to Long/Magerko (2020: 598), AI literacy comprises "a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace". In other words, AI literacy refers to the competencies that humans need in order to interact with AI in various situations, while, at the same time, maintaining a critical stance. Building on this understanding, Markauskaite et al. (2022: 3 f.) point out that the rapid development in AI requires learners to constantly develop new competencies. In their study, they reflect on such competencies from three perspectives: cognition, humanity and society (Markauskaite et al. 2022). From a cognitive perspective, it is suggested that, as AI transforms the way humans carry out cognitive tasks, it is necessary to learn how AI tools can augment learning, behaviour and intelligence. From a humanistic perspective, it is argued that AI should have human values in focus, both regarding the use of AI technology and their design. The social perspective, in turn, goes beyond the individual, focusing on sociocultural systems' competencies in using AI. A third AI literacy framework, which is of particular relevance to our thematic issue, is Krüger's (2023) professional machine translation (MT) literacy framework, which accounts for the competencies that professional translators need in order to integrate MT in their workflow.

In essence, while Long/Magerko (2020) and Krüger (2023) can inspire the design of future teaching scenarios with the integration of AI, Markauskaite et al. (2022) initiate a discussion about AI-related competencies needed in the workplace, in learning situations and for personal wellbeing. Our thematic issue, in turn, aspires to contribute to the growing body of research on AI and digitalization of communication practices with new knowledge about how the development may define HCI and help inform such competencies. To this purpose, the issue zooms in on the impact of AI on knowledge generation from the perspective of four different (but related) areas: translation, professional communication, university language teaching, and research into multilingual specialised communication. In each of these areas, GAI and large language models (LLMs) have disrupted the way knowledge is being generated and transferred. By examining and critically reflecting on selected examples of text generation and translation, the articles of the issue all address how the accelerating development of AI-powered tools impacts HCI, thus contributing to discussions about if and how AI technology acts "as a co-intelligence to improve (or replace) our work" (Mollick 2024: xix–xx).

<sup>1</sup> We use *expertise* with a reference to Bubeck et al. (2023), but we are highly sceptical of the idea that machines can possess expertise, understood as a "special skill or knowledge that is acquired by training, study, or practice" (Collins dictionary).

<sup>2</sup> It should be noted that authors differ regarding the terminology used about the skillset needed in connection with the use of AI. Markauskaite et al. (2022) use the term *capability*, while Long/Magerko (2020) use *competency* and Krüger (2023) uses *competence*. To ensure terminological consistency, we use *competency* throughout this introduction article.

Among the many areas of our lives that are impacted by GAI is the way we work professionally with language and specialised communication. According to Engberg/Fage-Butler/Kastberg (2023: 5), “the shape of a domain’s knowledge is based upon the communicative exchange between individual experts”; it is formed in an interactive process. In the words of Kastberg (2007: 8), “(...) communicative ‘positions’ converge on the (co-)construction of (specialized) knowledge.” This means that when GAI and LLM-based tools form part of this exchange, the digital tools form part of the co-constructive process, changing the very nature of how specialised knowledge is constructed. This, for instance, is the case in Virtual Reality (VR) and Augmented Reality (AR) professional training (language-based), automated environments in technical writing and terminology-database management, as pointed out by Alexander Holste in his article *The Model of Automated Knowledge Communication – Developing Specialized Communication Studies: An Outline* (this issue). Clearly, the development calls for adaption on the part of researchers, who must consider that digital tools are embedded in the construction of knowledge, a situation that Holste (2024) denominates *automated knowledge communication* (AKC). More specifically, AKC is characterised as a situation in which a communicator interacts with a digital device for the purpose of constructing expert knowledge to solve a real-life problem. Holste (2024) developed an AKC model that accommodates the evolving integration of AI/LLM-based technology into multilingual specialised communicative practices. In his contribution, Holste (this issue) presents the AKC model and discusses how it can be used as a platform for investigating how communicators interacting with digital tools can create expert knowledge. Drawing on an analysis of seven empirical studies, conducted by himself and others, Holste’s results contribute to discussions about the limits and affordances of GAI – one of the key competencies in Long/Magerko’s (2023) literacy framework – and about how the capabilities of GAI compare to human cognition.

AI chatbots have become essential tools in knowledge work, especially for creating and personalising content. Market projections from ContentServ<sup>3</sup> (n. d.) indicate that the text generation sector will grow at a compound annual growth rate of 17 % between 2022 and 2030. As mentioned above, organisations are using GAI tools across multiple areas, from answering customer inquiries to generating standard documents like order confirmations (Ferguson 2023: 39). According to Juniper Research (2022), chatbot messaging use is expected to nearly triple from 3.5 billion applications in 2022 to 9.5 billion by 2026.

Research shows both benefits and limitations of AI adoption in professional settings. Research by Cusnir/Nicola (2024) found that 75 % of Romanian PR companies use AI tools – mainly ChatGPT – and while these tools effectively reduce routine workloads, they also create new challenges. The study revealed that over 77 % of PR professionals use AI without formal training, leading to difficulties in using the tools effectively. Additionally, practitioners reported significant trust issues with AI outputs, citing frequent inaccuracies and emphasising the continuous need for human supervision and content verification. Training and trust issues seem to be widespread across the communication industry.

Henrik Køhler Simonsen’s study (this issue), *Generative AI: A Threat or a Catalyst for Communication Professionals?*, examines how communication professionals are adapting to GAI, based on a study of 102 survey respondents and 8 interviews with Danish communication professionals. The findings reveal that while professionals are using GAI for tasks such as

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<sup>3</sup> ContentServ is a company that provides AI-powered solution to enable product experiences for marketers, product teams and IT professionals (<https://www.contentserv.com/>).

generating texts, reviewing content, translation, generating ideas, and data analysis, the GAI use is generally limited. A key factor in this limited adoption appears to be the lack of formal training reported by 82 % of respondents, and instead they are relying solely on self-teaching methods. Consequently, many professionals feel underprepared for utilising the technology effectively, leading them primarily to use GAI as a “sparring partner” rather than a comprehensive tool for their work. Another factor relates to a lack of clear guidelines and formal processes, which these professionals need to use GAI effectively in their work.

Simonsen’s article introduces three practical frameworks to address the challenges: a Prompting Model for structuring effective prompts, a Task Model for categorising GAI applications and a Decision Support Tool for creating audience-targeted content. Using a theoretical framework combining human-machine communication theory, actor-network theory and lexicographic theory, Simonsen concludes that, while GAI adoption is rapid, it lacks proper structure in most organisations. According to Simonsen, success in the GAI era depends on professionals learning to master the technology effectively while maintaining their own unique thinking and creativity, suggesting that GAI could be either a threat or a catalyst, depending on implementation strategies and training approaches. The article’s findings highlight a critical gap in AI literacy among communication professionals, who mostly rely on self-teaching methods rather than formal training. The study’s three proposed frameworks for prompting, tasks, and decision-making offer practical tools for building essential AI literacy in the field.

The transformative impact of AI technologies on specialised communication extends beyond knowledge construction into the realm of professional education. As the technologies become increasingly embedded in professional workflows, they fundamentally reshape how specialised knowledge is communicated, stored, and transferred across disciplines (SCAI 2024, Taherdoost/Madanchian 2023). While AI tools offer new possibilities for enhancing specialised communication practices, they simultaneously create a competency gap between traditional educational outcomes and emerging workplace needs in specialised communication fields (UNESCO 2021). According to Luckin/Cukurova (2019) and Wei Dai/Suzuki/Chen (2024), the resulting pedagogical challenge lies in developing educational frameworks that can prepare students effectively for collaborative human-AI workflows while maintaining the critical ability to navigate complex specialised communication scenarios, often in multicultural workplaces.

In response to the competency gap, Marion Wittkowsky’s and Ralph Krüger’s article *Integrating Artificial Intelligence in the Higher Education of Technical Writers and Technical Translators* (this issue) examines how universities should adapt technical translation and technical writing in specialised communication curricula to prepare students for a professional world increasingly shaped by high-performing language-oriented AI technologies. Drawing on insights from both translation studies and technical writing research, the authors argue that successful navigation of today’s multilingual specialised communication landscape requires students to advance beyond traditional language proficiency to incorporate competencies in data handling and computational language processing. The article examines how the integration of LLMs is transforming traditional roles in technical writing and technical translation, necessitating new cross-professional competencies and deeper technological understanding. Building on frameworks such as the DataLit<sup>MT</sup> project (Krüger/Hackenbuchner 2022) and an AI literacy framework for translation (Krüger 2023), the authors demonstrate how language professionals must evolve beyond mere end users of AI systems to become active participants in system optimisation and workflow integration. The article maps out emerging competen-

cies needed in AI-enhanced workplaces, where technical writers and technical translators increasingly share common tasks in areas such as information research, text production and quality assessment. This analysis of required competencies provides valuable input for understanding the educational dimension of AI literacy, particularly through the lens of frameworks like Long/Magerko's (2020) AI literacy concept. By analysing how traditional technical translation and technical writing workflows are being disrupted by AI integration, Wittkowsky and Krüger identify essential competencies for human-AI collaboration in multilingual specialised communication contexts, directly contributing to the conceptualisation of AI literacy in this thematic issue.

In previous work, Krüger (2018) highlights the impact of automation on the competency profile of translators. He argues that, in augmented translation, the need for text production skills has diminished because translators are no longer translating from scratch. Instead, they have become post-editors, who must first read and understand the source text as well as the translation suggestions generated by machines, and then they must select the most appropriate solution, which may need to be edited or adapted for the target reader. Therefore, Krüger argues, the most important translator skill is text reception when GAI technology is complementing humans during translating. However, in order to be able to detect translation errors when interacting with machines, translators must have source and target language skills, subject-specific knowledge, the ability to plan the translation process, knowledge of translation norms, psycho-physiological skills such as memory and stress management, the ability to adapt to the demands of the translation task, and the ability to use translation tools, which reflects the five sub-competences outlined in the widely recognised Translation Competence Model developed by PACTE (2003).

Furthermore, there is no doubt that powerful technologies will (continue to) affect the work routines and cognitive processes of translators, challenging their roles and requiring new skill profiles. Translators have often felt threatened by the introduction of technology: for example, computer-aided translation tools in the 1980s, neural machine translation (NMT) since 2016, and GAI since 2022. Clearly, the introduction of the latter has initiated an ongoing debate among translators, and in society at large, as to whether AI will replace human translators (Christensen/Bundgaard/Flanagan 2024). Not least the paper *Achieving Human Parity on Automatic Chinese to English News Translation* by Hassan et al. (2018) has prompted a number of studies to determine whether we are at a point where machine output is indistinguishable from text translated by humans. Typically, scholars ask reviewers to assess translation quality in a blind review process. In doing so, they adopt an approach similar to the so-called Turing test. For instance, Yan et al. (2024) evaluated the translation quality of ChatGPT-4 against human translators of different levels of expertise in three language pairs (Chinese ↔ English, Russian ↔ English and Chinese ↔ Hindi) and three domains (news, technology and biomedicine). The study showed that the performance of LLMs is comparable to that of junior translators in terms of total errors made, but that intermediate and senior translators produce better translations than LLMs, and that LLMs tend to produce more literal translations compared with human translators. Other studies have started to compare NMTs and LLMs. Several have found that LLMs can outperform NMT systems (Jiao et al. 2023, Peng et al. 2023, Wang et al. 2023). Consequently, the quality of GAI translations may have reached a level where raw machine translations generated without human interaction may be sufficient, but this depends on a number of factors, such as the language combination, the type of text, the translation tool used, and the purpose of the translation. Due to the complexity of legal texts and the need

for expert knowledge, in the article *Maschinelle und menschliche Übersetzung im Vergleich am Beispiel des Entwurfs des ersten ungarischen Zivilgesetzbuches (Deutsch – Slowakisch)* (in this issue), Peter Gergel et al. hypothesise that humans are still needed in the legal translation loop. In their study, Gergel et al. compare a translation of a law text produced by a professional translator and a legal expert in combination with machine translations generated by Google Translate, DeepL, eTranslation and ChatGPT, focusing on their ability to transfer accurately the inherent expertise by means of terminology. Thus, the study deals with a genre in which a correct and precise translation of the target text is generally expected, which can be difficult to achieve because legal terms are rarely fully equivalent in two languages. Legal translation is therefore considered a very demanding task, even for human beings. Gergel et al. conclude that machines have not yet reached human parity for terminological units consisting of one, two, three or four words. Interestingly, the study shows that different GAI tools make different types of errors. This highlights the necessity for translators to acquire advanced MT/AI skills to be able to detect errors when post-editing MT output.

Finally, in an article entitled *Do Translators Dream of Electric Brains?*, Ricardo Muñoz Martín (this issue) reviews and compares the capabilities of AI-powered technology and human brains, with a view to ascertaining the impact on the translation profession. Establishing that human thinking is essentially metaphorical and that this has shaped our perception of the world, Muñoz shows that metaphorical thinking can lead to serious oversimplifications and misconceptions – for instance, when our understanding of translation (and communication) builds on the conduit metaphor, leading us to believe that meaning is objective and that meaning can be transferred flawlessly and unchanged from one brain to another. A prevalent metaphor for AI is similarly deceptive because it compares the intelligence of a brain, a biological organ capable of cognitive functions, to that of a computer, defined as a machine with a computational processing device powered by electrical signals. The processes of AI-powered technology, based on so-called artificial neural systems, are generally assumed to be similar to those of a human brain, but Muñoz is adamant that this is very far from the truth. Even if AI-generated output can now emulate professional translation quality, the technology still depends on statistical correlations and still lacks any real-world knowledge (cf. also Schjoldager et al. 2023). By way of conclusion, Muñoz dismisses as fundamentally flawed the idea that AI systems can now replace professional translators. As he sees it, a main problem for the translation industry is a fear of missing out on profits if they do not go along with the trend of increasing digitalization processes. Consequently, though the technology will increasingly augment human translators' capabilities to produce high-quality translations, there is no reason to expect that the services of professional translators will no longer be required. Therefore, according to Muñoz, translators really do not dream of an electric brain.

Summing up, the articles of this thematic issue explore different perspectives on human interaction with technology in text production and translation. It is our hope that the issue contributes with new knowledge that may help inform the competencies that humans need in order to critically reflect on AI technologies, communicate and interact with AI technologies, and using AI technologies for various purposes.

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# The Model of Automated Knowledge Communication – Developing Specialized Communication Studies: An Outline

*Alexander Holste*

**Abstract** The Model of Automated Knowledge Communication outlined in this article aims to broaden the scope of current conceptualizations of specialized communication to account for self-adapting, AI-/LLM-based machines. These machines are presently changing the practice of multilingual specialized communication in fundamental ways – hence necessitating research to adapt. The model facilitates the development of specialized communication studies specifically by integrating, firstly, new approaches toward concepts of expert knowledge and, secondly, the involvement of sophisticated machines able to act increasingly autonomously. In order to conceptually account for the latter, the model extends the discourse of specialized communication to approaches of cybernetics, technical sociology, and media sociology. The paper starts with an overview of the objects of research the model can be applied to.

**Keywords** AI Literacy, Chatbot, Controlled Language, Human-Machine Interaction, Knowledge Communication, Large Language Models (LLM), Neural Machine Translation (NMT), Parallel Corpora, Robot, Rule-Based Machine Translation (RBMT), Specialized Communication, Technical Documentation

## 1 Introduction

The construction of knowledge is the communicative aim of many communicative situations and it determines the type of relationship between the communicating parties. The means to reach this communicative aim are specific types of knowledge communication (*Formen der Wissenskommunikation*). These are increasingly set in multilingual and/or multimodal contexts as well as being progressively informed by the participation of machines promoting automatization processes. An increased focus on machines participating in interactive processes – so-called human-machine interaction (*Mensch-Maschine-Interaktion*, Womser-Hacker 2020: 527) – can be observed in areas of specialized communication studies (*Fachkommunikationswissenschaft*; Schubert 2007: 347–348; Heidrich/Schubert 2019: 57–62), respectively knowledge communication research (Engberg/Fage-Butler/Kastberg 2023: 6–10).

The most discussed examples are AI-based/self-adaptive, rule-based, or hybrid human-machine interaction<sup>1</sup> like interaction with chatbots, devices, robots, cobots, and so forth; Rule

<sup>1</sup> Rule-based systems are systems created by software engineers that intentionally decide which units of information, i. e. linguistic entities, correspond to each other. These units are, for example, question-answer pairs or matching linguistic pairs of two individual languages in translation processes. In contrast, in AI-based/self-adaptive systems, algorithms substitute the process of intentional decision making

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Based Machine Translation (RBMT) and neural machine translation (NMT), virtual reality training and augmented reality training on the job (language-based), automated environments in technical writing, translation memories, terminology databases, controlled languages, parallel multilingual domain specific corpora, the usage of speech-to-text transformers et cetera. It seems quite apparent that this research must be interdisciplinary because issues belonging to the realms of linguistics, translation studies, and technical communication are as relevant here as are approaches of technical disciplines (e. g., cybernetics, information sciences). Accordingly, on the one hand, any attempt to comprehensively conceptualize these perspectives affords a multi-faceted theoretical approach. On the other, any investigation in the field of automated knowledge communication relies on methods adopted from these feeder disciplines.

The current lack of attempts to innovate the perspectives of specialized communication studies, respectively knowledge communication research, considerably limits the scope of research in this discipline so that it runs the risk of marginalization. To counter this, this paper investigates the central research question, how actors (*Wissensakteure*) that draw on language processing machines construct expert knowledge (*Fachwissen*; Kalverkämper 1998) in Automated Knowledge Communication (AKC). This entails the following sub-questions:

1. What is the scope of empirical research on AKC with a focus on mono- or multilingual objects of research?
2. How must already existing models of multilingual specialized communication studies (*mehrsprachige Fachkommunikationsforschung*) be revised to be able to incorporate issues of automated knowledge communication? Conversely, which elements of already existing models can feature as a basis to better grasp these issues in the context of a new model?
3. How can the communicative construction of knowledge be modelled to incorporate human-machine interaction at the individual as well as at the level of (expert) culture?

Developing the Model of Automated Knowledge Communication (AKC model) has the aim to advance the discipline of specialized communication studies/knowledge communication research by facilitating the conceptualization and empirical investigation of the new developments mentioned above. A model's scope and purpose determine "the degree of applicability, the degree of abstraction of the model components, the degree of formalization of the model and the degree of transferability" (Heine/Schubert 2013: 102, translation by AH). As models often serve various purposes, any overview of their comparability must be clearly limited (Heine/Schubert 2013: 102). Hence in this paper the overview mainly presents those model elements and modes of operation that provide an answer to my second and third sub-question as stated above.

## 2 Scope of empirical research on automated knowledge communication

This section deals with the first sub-question. Multilingual specialized communication studies investigate automated knowledge communication, i. e., human-machine interaction. Being part of specialized communication, automated knowledge communication is defined by the following four criteria:

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by statistical frequency to determine which linguistic entities follow each other. Hybrid systems combine both system architectures.

- Expert knowledge is constructed by an actor in a situation in which the actor interacts with a machine within the same time frame (synchronously) and both are physically present although it is also possible that additional actors are physically present whereas others participate digitally.
- A real-life problem is the object of interaction. The expert knowledge gained during the interaction enables the actor to solve it.
- The interaction is based on natural, and perhaps also on controlled language, that may also be accompanied by other modes of communication like pictures or body movements.
- The interaction involves a machine that processes and operates with partial autonomy as a participating entity in the knowledge construction process.

These criteria can be specified and operationalized by the following three parameters:

1. degree of abstraction with the features *micro level of AKC*, *meso level of AKC* and *macro level of AKC*;
2. degree of self-adaptivity with the features *rule-based*, *self-adaptive* and *hybrid machines*;
3. degree of multilingualism with the features *monolingual* and *multilingual*.

Based on these parameters, research on AKC can be systemized as follows:

Table 1: Synopsis of parameters informing research on automated knowledge communication

Degree of abstraction	Degree of self-adaptivity	Degree of multilingualism (monolingual)	Degree of multilingualism (multilingual)
individual knowledge and individual knowledge of specialized language	rule-based	field 1: rule-based human-bot-interaction field 2: rule-based systems of technical documentation field 3: monolingual rule-based human-device interaction/human-robot interaction; collaborative robots/cobots; VR/AR devices	field 8: pre- and post-editing of rule-based machine translation (RBMT)
	self-adaptive	field 4: monolingual AI-based human-device interaction/human-robot interaction; industry 4.0; collaborative robots/cobots; Internet of Things; VR/AR devices field 5: human-bot interaction depending on AI-based parsing & prompting field 6: autonomously adaptive interacting systems, semi-supervised machine learning	field 9: simultaneous machine interpretation or machine translation (RBMT & NMT) field 10: written neuronal machine translation (NMT) with/without pre- and post-editing
	hybrid	field 7: hybrid adaptive interacting systems, unsupervised machine learning	field 11: NMT coupled with terminology database management
expert knowledge (of language)	/	field 12: controlled languages	field 13: parallel multilingual domain-specific corpora
general language knowledge	/	field 14: monolingual semantic-lexical nets and their coupling by an intermediate language	field 15: general language translation memories

Table 1 presents prototypical fields of empirical studies based on relevant publications within the scope of investigation and research results. These fields outline the scope of empirical research on AKC. The overview is therefore not conclusive.<sup>2</sup> For further details, please see Holste (2024a: 52–97), which summarizes more than 100 specific empirical studies.

<sup>2</sup> This overview is not a meta-study because it features as the starting point for the AKC model and for the answer to the central research question of this paper. It thus neglects conventions of empirical methodology.

### 3 A focused survey of German multilingual specialized communication studies

This section answers the second sub-question. It gives a brief overview on German multilingual specialized communication studies, which, on the one hand, sketches relevant tenets which served as an inspiration for the AKC model. On the other, the survey identifies research deficits in order to be able to adequately conceptualize the changed research object. In this way, the second sub-question is answered.

Obviously, all academic disciplines have a history of paradigms, theories, models, and methods that define their nature. The makeup of a research discourse is determined by its discipline (Foucault 2017 [1971]). Generations of scientists have advanced the methods, knowledge, and structures of a particular discipline culminating in the idea that the present stands like a dwarf on the shoulder of giants (usually attributed to Bernard of Chartres, † 1126, quoted by Hoffmann/Kalverkämper 1998: 356). Though perhaps intended as a humble nod of respect towards tradition, this notion also implies steady progress, thus running the risk of downplaying paradigm shifts (Kuhn 2012 [1962]) occurring in light of current research findings. Irrespective of how this relation between past and present thinking is understood, it stands to reason that (scientific) thinking relies on presuppositions. Argumentations manifest in texts always have a social-historical background – as is argued by critical social theory (*Kritische Theorie*) (Habermas 1971). Selective processes informing the development of a rationale are grounded in the historical background of a discipline that provides the context in which a text and its argumentation must be seen. The discipline at the background of the AKC model are mono- and multilingual specialized communication studies.

The AKC model has its roots in the, by now, classic works on LSP, specialized text linguistics and first cognitive approaches by Hoffmann (1985 [1976], 1988, 1993), Kalverkämper (1990, 1998), Baumann (1996, 2004), and Budin (1996), who contributed to issues of expert knowledge and specialized communication. Yet, it also draws on models and approaches that are of a more process-oriented nature, for example, as concerns writing processes (Göpferich 2002) and processes of professional communication and specialized translation (*professionelle Kommunikationsarbeitsprozesse*; Schubert 2007, Risku et al. 2011, Engberg/Fage-Butler/Kastberg 2023). Krüger's (2021) model conceptualizing processes of neural machine translation must also be mentioned as it serves as a transition away from traditional specialized communication studies and towards innovative approaches that focus on the characterization of automated processes. Likewise, relevant approaches in cybernetics (Wiener 1989 [1950], Frank 1964, von Cube 1970 [1967]) contribute to the making of the model as do approaches focusing on the action-theoretical differentiation between humans and machines in communication contexts (Schulz-Schaeffer 2017) and a theory on the acceptance and usage of technology (Venkatesh et al. 2003).

### 4 The Model of Automated Knowledge Communication

This section discusses the third sub-question. The AKC model was developed by Holste (2024a). It is based on the results of the previous research review, most prominently Kalverkämper (1998), Baumann (1996, 2004), and Budin (1996). It is defined as follows:

The term automated knowledge communication applies to language-based interaction between a situated actor (*Situierter Wissensakteur*) and a situated language processing machine in which an unsituated actor (situated instead in the larger interaction context; *Entsituierter Wissensakteur*) indirectly participates. This interaction enables the situated actor to perform

cognitive-emotive processes, thus constructing expert knowledge in order to be able to solve a real-life problem. As shown in Figure 1, this situated actor may complement the interaction when he/she mediates between an actor of a previous communication (*Wissensakteur der Vorkommunikation*) and an actor of a follow-up communication (*Wissensakteur der Anschlusskommunikation*).

In principle, the model, summarized in Figure 1, differentiates between ‘situation (s)’ and ‘context/unsituated (u)’. While the former requires physical co-presence and synchronicity, the latter is a container word for actors, acts and individual cognitive processes that do not take place in the actual situation being investigated. The AKC model is based on three interactive/communicative constellations: the ‘interaction triangle’ (*Interaktionsdreieck*), elaborated by the ‘communication square’ (*Kommunikationsviereck*), on the one hand, and by the ‘mirrored communication square’ (*gespiegeltes Kommunikationsviereck*), on the other hand.

The conception of an interaction triangle comprises the three model elements ‘situated actor – A (s)’, ‘machine – MAS (s/u)’ – and ‘text in a broad sense’ (*Kommunikat/Translat*). The focus is on the interaction between ‘situated actor – A (s)’ and ‘machine – MAS (situated/unsituated)’ when constructing a ‘text in a broad sense’. This text always consists of language, yet it may also incorporate as further means of rendering information (Expression/E) visualizations such as static/dynamic pictures, sounds, body movements and logico-semantic relations between those modalities in a medium (M) such as a book, a website, a machine display and speakers etc. The first elaboration of the interaction triangle includes the fourth model element ‘unsituated actor – A (u)’ to create a communication square with knowledge construction of the ‘situated actor – A (s)’ at its core (on the left-hand side of Figure 1). The second elaboration of the interaction triangle, the conception of a mirrored communication square, consists of the four elements: ‘situated actor – A (s)’, ‘actor of previous communication – A (prior)’, ‘actor of follow-up-communication – A (fo)’, and ‘text in a broad sense’ (on the right-hand side of Figure 1). The mirrored communication square is brought about by the communicative function of the ‘situated actor – A (s)’ to mediate between ordering parties (represented by the model element ‘actor of previous communication – A (prior)’) and recipients (model element ‘actor of follow-up-communication – A (fo)’) when producing a ‘text in a broad sense’.

For example, a translator or technical editor can use a ‘machine – MAS (s/u)’ to compose a manual. The following processes taking place between all elements (with and without first and second elaboration) are captured in the model: on the one hand, processes involving various ‘levels of action’ (*Handlungsebene*) such as interiorization (*Interiorisieren*), exteriorization (*Exteriorisieren*) and control (*Lenkung*), on the other, cognitive-emotive processes taking place at the ‘actor level’ (*Akteursebene*).

In the following, the model element ‘situated actor – A (s)’ is explained as a representative of the model entity ‘actor’. The co-construction of knowledge by the ‘situated actor A (s)’ is central. To this avail, the ‘situated actor A (s)’ interiorizes information provided by the ‘text’ as generated by the ‘machine – MAS (situated/unsituated)’. The ‘situated actor A (s)’ then constructs (see Figure 2) expert knowledge drawing on internal processes, which are the ‘situated actor’s – A (s)’ sub-elements ‘body’ (*Körper*), ‘motivation’ (*Motivation*), ‘expectations and intentions’ (*Erwartungen und Intentionen*), ‘prior and expert knowledge’ (*Vor-/Fachwissen*), ‘competence’ (*Kompetenz*) and ‘acceptance’ (*Akzeptanz*). The sub-elements ‘body’ and ‘acceptance’ – particularly in relation to the role of emotions – emerge as novel elements and offer new vantage points on the research object.

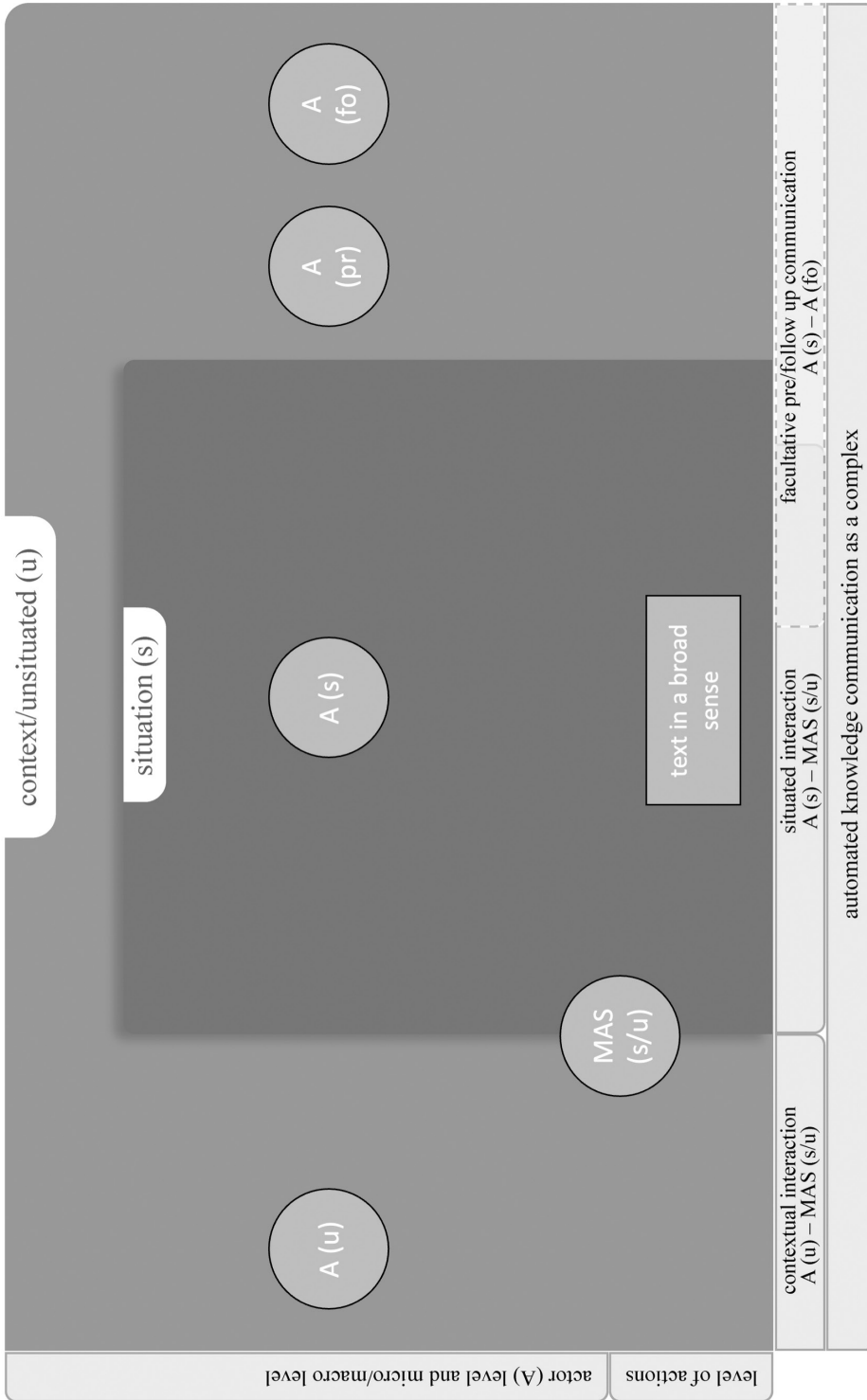


Figure 1: Elements of the AKC model

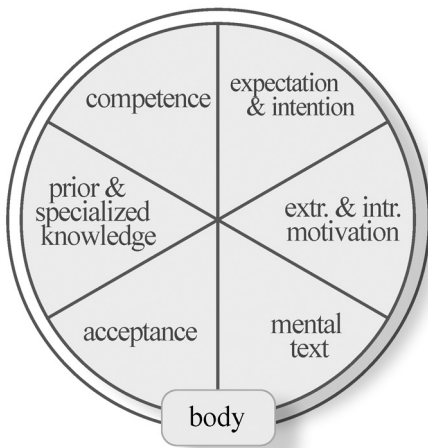


Figure 2: Element ‘situated actor – A (s)’ as part of the AKC model

Of central relevance are the degrees to which the ‘machine – MAS (situated/unsituated)’ and the ‘unsituated actor – A (u)’ contribute to the ‘situated actor’s – A (s)’ construction of knowledge (see Figure 3): The degree to which either ‘machine – MAS (situated/unsituated)’ or the ‘unsituated actor – A (u)’ contribute to the text production and indirectly to the ‘situated actor’s – A (s)’ construction of expert knowledge is inversely proportional depending on whether the ‘machine – MAS (situated/unsituated)’ features the sub-element ‘self-adaptive algorithm’ (*‘Selbstadaptiver Algorithmus’*) or ‘hybrid algorithm’ (*‘Hybrider Algorithmus’*). Moreover, the degree to which the ‘machine – MAS (situated/unsituated)’ is allowed to contribute to the construction of meaning also heavily depends on the ‘situated actor’s – A (s)’ sub-element ‘acceptance’, thus highlighting the relevance of the attitude, i. e. the emotive aspect of interaction. Conversely, the degree to which the ‘unsituated actor – A (u)’ contributes rises inversely if a ‘machine – MAS (situated/unsituated)’ features the sub-element ‘rule-based algorithm’ (*‘Regelbasierter Algorithmus’*). Of course, individual exceptions are possible.

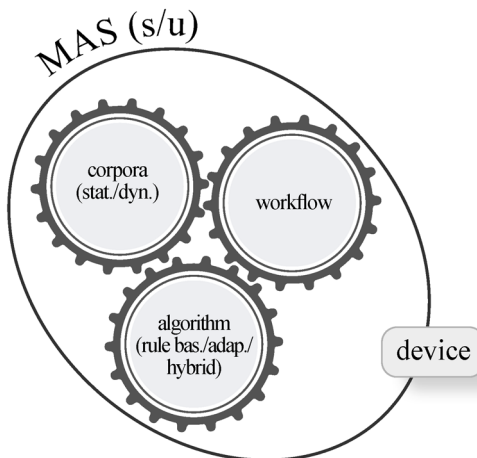


Figure 3: Element ‘machine– MAS (s/u)’ as part of the AKC model

Whether a ‘machine – MAS (situated/unsituated)’ is to be associated with the ‘level of actions’ or the ‘actor level’ must be decided individually. Yet rather than focusing on deficits, it should be noted that the ‘level of actions’ and the ‘actor level’ make it possible to assess the ability of the ‘machine – MAS (situated/unsituated)’ and its bearing on the ‘situated actor’s – A (s)’ construction of knowledge gradually for each individual case by taking into account the respective sub-element ‘algorithm (rule-bases/self-adaptive/hybrid)’ of the ‘machine – MAS (s/u)’. When conceptualizing the model element ‘machine – MAS (situated/unsituated)’, I have chosen such a comparatively high level of abstraction for the AKC model because the rapid improvement of language processing machines would otherwise likely soon render it obsolete (obsolescence of NLP machines). A ‘machine – MAS (situated/unsituated)’ with the sub-element ‘rule-based algorithm’ issuing text modules belongs at one end of the scale. This type of ‘machine – MAS (situated/unsituated)’ features rather at the ‘level of actions’ than at the ‘actor level’ and entails the overlap between the model elements ‘machine – MAS (situated/unsituated)’ and ‘text’. At the other end of the scale, a ‘machine – MAS (situated/unsituated)’ with the sub-element ‘self-adaptive algorithm’ would be positioned, whose sensors would register the ‘situated actor’s – A (s)’ sub-element ‘body’ immediately while the ‘text’ would provide a mediated stimulus. Such a ‘machine – MAS (situated/unsituated)’ would rather – although not wholly – be located at the ‘actor level’ – as is the case for all types of machines conceptualized here. This is due to the features that machines are as yet missing. Similar to the type of algorithm, the sub-element ‘corpora (static/dynamic)’ of the ‘machine – MAS (situated/unsituated)’ can also help to determine whether an individual case belongs rather to the ‘level of actions’ or to the ‘actor level’. ‘Micro level’ refers to the level of a micro culture as a community of interest or else Community of Practice (CoP), whereas ‘macro level’ refers to the macro culture of an individual language, a legal sphere etc. (see Figure 4).

The applicability of the Model of Automated Knowledge Communication is illustrated by seven examples (Holste 2024a: 301–336):

- Example 1, derived from Holste (2023a), applies the communication square of the AKC model to a case taken from a monolingual domain and employing a rule-based system. This example addresses the interaction of clients looking for a job with the chatbot of the Missouri Department of Labor and Industrial Relations.
- Example 2, derived from Azaria (2022), shows how the communication square of the AKC model can be applied in the monolingual domain to a case with a self-adaptive system. The focus is here on an investigation of an user’s interaction with the chatbot ChatGPT under laboratory conditions to check the chatbot’s limits, especially regarding wrong answers.
- In Example 3, derived from Holste (2024b), the communication square of the AKC model is applied in a multilingual domain to a case in which a self-adaptive system is at work. This example investigates the website [corona.duesseldorf.de](https://corona.duesseldorf.de) of the city of Duesseldorf, translating its German content simultaneously and fully automated into English and Italian by a Google-Translate-API. The example shows its usage by a citizen to gather information about COVID-Pandemic regulations.
- Example 4, derived from Holste (2023b), illustrates the mirrored communication square of the AKC model also in the multilingual domain, but in a case where a self-adaptive system is used. It deals with the interaction between a technical translator and the NMT-Machine-Microsoft® Translator with the purpose to translate requirements of a tender specification in the domain of tenders for public transport.

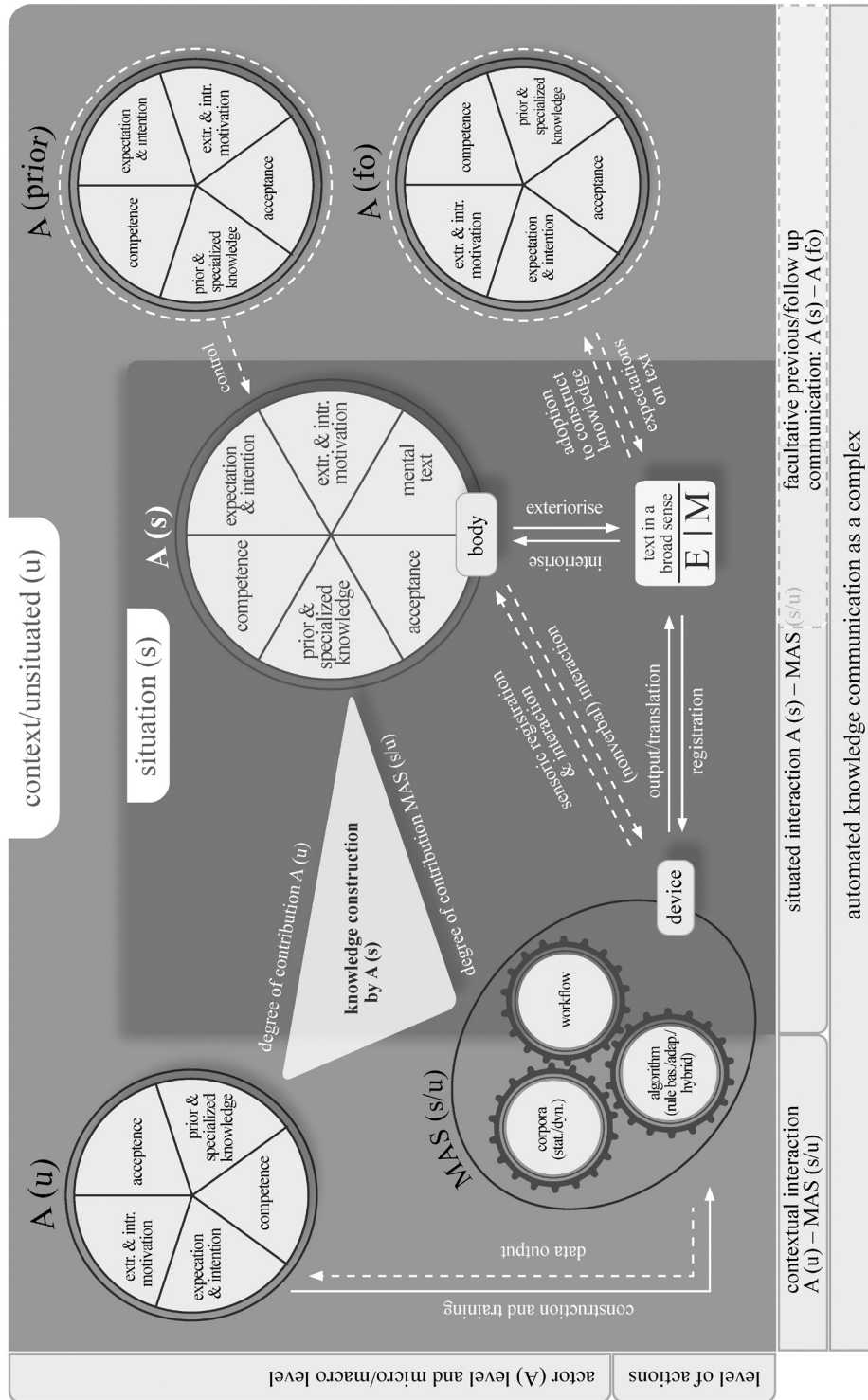


Figure 4: Model of Automated Knowledge Communication

- Example 5, derived from Paletta et al. (2019), demonstrates the AKC model processes ‘sensoric registration & interaction’ and ‘nonverbal interaction’. This example focuses on the employment of the healthcare robot Pepper in a home for elderly people.
- Example 6, derived from Dohmen/Geisler/Holste (2022), points out the model process ‘construction and training’ taking place between ‘unsituated actor – A (u)’ and ‘machine – MAS (s/u)’.
- Example 7, based on Wittkowsky (2022), shows – similarly to example 4 – specialized translation processes, but deals with rule-based systems instead of NMT-based systems.

Furthermore, the AKC model served as a point of departure for two PhD projects: Schenda’s (2024: 25–30) PhD thesis modifies the model from the perspective of technical documentation, especially model elements ‘interaction triangle’, ‘situation’ and ‘context’: His work focuses on users who work with a technical product using the manual of that technical product. Schenda (2024: 218–225) takes an empirical stance when he applies the modified model to user situations with three technical products: a hand blender, a fully automated coffee machine, and an audio system. Matthäi’s PhD project (in prep.) empirically investigates user-carebot interaction with a focus on embodiment as part of multimodal communication. His project elaborates and modifies the interaction triangle of the AKC model: the sub-elements of the elements ‘situated actor A (s)’ and ‘machine – MAS (situated/unsituated)’; and the relation between ‘body’ and ‘device’. The project is based on Matthäi’s master’s thesis that has already garnered considerable attention in the specialized press (Informationsdienst Wissenschaft 2024, Health & Care Management 2024, Silicon Saxony 2024, and so forth).

## 5 Conclusion

To conclude, the AKC model provides the means to answer the central research question, how actors that draw on language processing machines construct expert knowledge in AKC: The AKC model and the definition of automated knowledge communication presented above express a shift of vantage point in that they integrate language-based human-machine interaction into a concept of communication.

The AKC model invites multilingual specialized communication studies to conceptualize how technological change has modified their scope of research in order to facilitate further investigation. This paper attempts to point out why human and machine need not be understood as a dichotomy as conceptualized, for example, by Dreyfus/Dreyfus (1986) because their collaboration bears both potential benefits, but also limits. An open discussion of this topic would benefit the general perception of specialized translation just as much as would multilingual specialized communication studies. Accordingly, the model allows a categorization of research carried out in the various components making up its scope of investigation. Also, elaborations or modifications of model elements might be worthwhile. The AKC model points to several issues of possible interest for further research, of which I would like to single out only three here:

- It could be further investigated in which ways the element ‘body’ influences how a ‘situated actor – A (s)’ constructs a ‘mental text’.
- Also a closer investigation of the element ‘text in a broad sense’ with a view on its sub-element ‘corpora (static/dynamic/hybrid)’ should yield important new insights. I would like to argue not in favor of research undertaken from the vantage point of en-

gineering, but from that of specialized communication studies. Hence, the increase or decrease of text quality, especially as regards its functional-pragmatic dimension, is of central interest. For if, in the future, a corpus will be increasingly based on faulty texts produced by the machine itself and not post-edited by humans, it must be assumed that the quality of the corpus and with it the quality of texts automatically generated from it will increasingly decline. Such an effect has already been observed for search engine algorithms. It is, of course, also possible that text quality enhances because engineers train machines, work at the corpus/and or modify algorithms.

- Future self-adaptive machines will probably be developed to create the illusion of a seemingly ‘real conversation,’ for example, by being able to small talk, to imitate turn-taking, to fake emotions etc. If these phenomena really occur, it must be empirically investigated if the behavior of ‘machine – MAS (s/u)’, first, provokes a high degree of ‘acceptance’ and, second, a high degree of participation of ‘machine – MAS (s/u)’ in the construction of knowledge.

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# Generative AI: A Threat or a Catalyst for Communication Professionals?

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**Abstract** Throughout history, humans have experienced numerous transformative events. Currently, we are experiencing a new disruptive event, generative artificial intelligence (GenAI). The research objectives of this article are to analyse and discuss how communication professionals use GenAI in their work, to analyse and discuss to what extent communication professionals have the required knowledge and skills to use GenAI optimally, and finally to analyse and discuss what type of help communication professionals need in their GenAI communication practices. The article draws on quantitative and qualitative data from an online survey of communication professionals and on qualitative interview data from eight semi-structured research interviews. The analysis was framed by a specially developed human-machine communication network model, referred to as the HMC network model, and a thematic analysis. The analysis showed that GenAI tools are widely known by communication professionals, but that they still do not seem to use GenAI optimally when researching and writing. The analysis also indicated that communication professionals need GenAI competencies and training, and that they need models, frameworks, and guidelines on how to use GenAI. The article presents the HMC network model and three GenAI support tools designed to help communication professionals use GenAI in their communication practices.

**Keywords** generative artificial intelligence (GenAI), GenAI decision support tools, human-machine communication (HMC) and lexicographic meaning construction processes (LMCP)

## 1 Introduction and Research Objectives

Generative artificial intelligence (GenAI) has taken the world by storm and has had a dramatic effect on communication practices. From a communication professional's point of view, GenAI might even be characterised as a disruptive and exponential technology (Christensen 2013). For instance, a recent survey by Humlum/Vestergaard (2024) with more than 100,000 Danes indicates that ChatGPT has been adopted with lightning speed in different professions, especially among journalists and marketing professionals.

GenAI is already disrupting a multitude of services, markets, and professions, and is accelerating the digitalisation of communication practices (Andersson 2023, Sharples/Pérez 2022, Simonsen 2023a). It has, therefore, had an important impact on the communication profession within a short time, but the question is whether the technology is a threat or a catalyst for communication professionals.

Notably, previous studies have mostly focused on the productivity effects. For instance, based on a survey with 444 college students using ChatGPT, Noy/Zhang (2023: 1) concluded that “time taken decreases by 0.8 SDs and output quality rises by 0.4 SDs”, indicating that

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ChatGPT substantially raises average productivity. Noy/Zhang (2023) further argue that the use of ChatGPT leads to the reduction of inequality between workers since low-ability workers can be used more extensively, and because the use of ChatGPT will enable people to restructure the tasks “towards idea-generation and editing and away from rough-drafting” (Noy/Zhang 2023: 1). Similar conclusions were reached in other studies, for example Dell’Acqua et al. (2023), who reported on 40 % productivity gains among Boston Consulting Group consultants, and Cambon et al. (2023), who reported similar productivity gains in a survey with management consultants and programmers. Finally, and by contrast, Baron (2023: 1) convincingly argued for a more critical view on GenAI, referring to it as “the lure of efficiency” and noting that GenAI may pose a serious threat to human writing as a discipline. This somewhat resembles Chomsky’s harsh criticism of GenAI as “High-Tech Plagiarism” (Chomsky 2023).

In other words, there seems to be a need for more research focussing on communication professionals and their changed practices and on the practical consequences of the GenAI disruption. Furthermore, there also seems to be a need for developing AI-assisted frameworks or models designed to help communication professionals in their daily work. Consequently, this article focuses on GenAI and the practices of communication professionals and contributes to this research area with insights into how communication professionals use GenAI tools.

Based on primary quantitative and qualitative survey data (N = 102), primary interview data (N = 8), and relevant theoretical contributions, this article analyses and discusses the following research questions:

- RQ 1: How do communication professionals use GenAI in their communication practices?
- RQ 2: Do communication professionals think they have sufficient knowledge and skills to use GenAI in their communication practices?
- RQ 3: What type of help do communication professionals need in their communication practices?

## 2 Research Philosophy and Methodology

The article’s research philosophical approach, understood here as the overall system of beliefs and assumptions about the research presented, is interpretivism (Saunders/Lewis/Thornhill 2019: 148). The purpose of the article is thus to “create new, richer understandings and interpretations of social worlds and contexts” (Saunders/Lewis/Thornhill 2019: 150). Using an interpretivist approach also means that survey and interview data are interpreted and constructed as products of human understanding and interpretation, and that the author recognises that his own values and beliefs play a role in the research process.

A mixed method design was used, triangulating insights by means of a quantitative method collecting survey data and a qualitative method collecting interview data (Saunders/Lewis/Thornhill 2019:181). Both survey data and interview data were collected from a Danish population. Both deductive and inductive reasoning was applied, which means that, on one hand, theoretical considerations were used to interpret and understand the collected empirical data and that, on the other hand, empirical data were used to develop new theoretical considerations.

The data collection techniques applied included an online survey with both quantitative, closed questions and qualitative, open-ended questions sent to a specific and carefully select-

ed sample of respondents (purposive sampling), followed by semi-structured research interviews with communication professionals. This allowed the author to explore specific topics or responses further during the interviews. The mixed method approach was used because a combination of both quantitative and qualitative data was particularly suitable for the analysis and discussion of the three research questions.

The online survey was used to collect data from a population of communication professionals, translators, and marketing professionals. A link to the survey form was sent to 300 potential respondents in Denmark and 209 responses were received ( $N = 209$ ), which means that the response rate was 69 %. The online survey was open for two months and included 4 closed multiple choice questions, 8 closed Likert scale questions and 6 open-ended questions. No demographic data about the survey participants were collected. For this research, a total of 107 responses were excluded, because these responses came from translators and marketing professionals, which means that 102 responses were included in this study ( $N = 102$ ).

Afterwards, semi-structured interviews were used to collect qualitative data from 8 selected communication professionals. The communication professionals selected for interview all work in the Danish communication profession and are “producing,” “strategic” and “managerial” communication professionals, which are expressions used about different types of communication professionals in a large survey published by the Danish Union of Communication and Language Professionals (Kommunikation og Sprog 2023). Furthermore, the selected communication professionals come from large and small companies, communication offices, and the public sector. An interview guide consisting of 12 questions was used. The interview questions were all open-ended questions encouraging the interviewees to elaborate and provide examples of relevance for the analysis. The interviews were conducted either face-to-face or by means of MS TEAMS and recorded.

The qualitative survey data and the interview data were uploaded to NVivo (Lumivero 2024), which is a research tool designed to assist researchers in conducting qualitative data analysis. The data were coded using the CAQDAS method, which is a technique that enabled the author to fragment, interpret and generalize data (Saunders/Lewis/Thornhill 2019: 651). After having prepared and conducted a preliminary analysis of the empirical data, a thematic coding scheme comprising 15 themes was devised with a view to analysing and discussing the three research questions. 5 themes were defined for each research question. The thematic coding scheme was subsequently used in NVivo to code and categorise statements from the online survey and the interviews allowing the author to systematically extract relevant data for analysis and discussion of each theme. The thematic coding scheme and the alignment of the research questions and the themes appear from Tables 2, 3 and 4 below.

### 3 Theoretical Framework

Communication and GenAI research have traditionally followed independent paths and veins of thinking. GenAI research has focused on how to make machines generate “aspects of human intelligence” and how to generate text (Guzman/Lewis 2020: 70), while communication research has focused on the human process and on how people exchange messages with each other (Guzman/Lewis 2020: 71). However, GenAI technologies are increasingly conversational, which means that the GenAI tool itself has become an important and integral actor in modern communication practices. Consequently, a multidisciplinary approach is needed to analyse and understand GenAI-assisted communication practices.

This article draws on Human-Machine Communication (HMC) theory, which is a line of thought within communication research. HMC is defined as “the creation of meaning among humans and machines” (Guzman 2018: 1) and is a theory that attempts to cast new light on people’s interactions with technologies such as GenAI tools. Another and somewhat wider definition is offered by Etzrodt et al. (2022: 440 f.), who argue that “HMC is seen as a process of message exchange between humans and machines, and its associated meaning-making, relationships, and social behaviour, embedded in different layers of social context on micro level, meso level, and macro level.” This wider definition allows us to see different aspects of HMC occurring at various levels, which is highly relevant in a study of communication practices and of the exchange and construction of meaning between human communicators and GenAI.

HMC theory is relevant for the analysis and discussion of the research questions defined above, as it helps us grasp the creation of meaning between communication professionals and GenAI. Both Guzman’s (2018, 2020) and Etzrodt et al.’s (2022) approaches can contribute to our understanding of how communication professionals use GenAI in their communication practices (RQ1) and to determining whether communication professionals have the required knowledge and skills to use GenAI (RQ2). Finally, the theoretical approach is also used to identify what type of help communication professionals need in their GenAI communication practices (RQ3).

The article also draws on lexicographic theory (LT). LT is used as a way of understanding the different task-based communication practices of communication professionals and is used as an architectural framework focusing on what communication professionals need in a specific situation to solve a specific task (Simonsen 2023a, 2023b, 2024, Tarp 2023). Furthermore, LT is used to go beyond language and analyse the meaning constructions between the human user, the GenAI tool and the communication product in line with the HMC theory. To this end, the “LMCP approach” is used (Leroyer/Simonsen 2020: 186). LMCP stands for *lexicographic meaning construction processes* and is defined as “the critical study, construction, interpretation and sharing of meaning mainly triggered by lexical items” (Leroyer/Simonsen 2020: 186). Modern LMCP theory thus facilitates the analysis of meaning constructions based on lexical items, upon which all communication practices rest.

The human interaction with a GenAI tool to produce a given communication product is a highly complicated process, and there seems to be a need for understanding how communication professionals interact with GenAI tools and a need for understanding what this means for the actual communication product. To be able to analyse and discuss the research questions, a HMC network model was developed (shown in Figure 1).

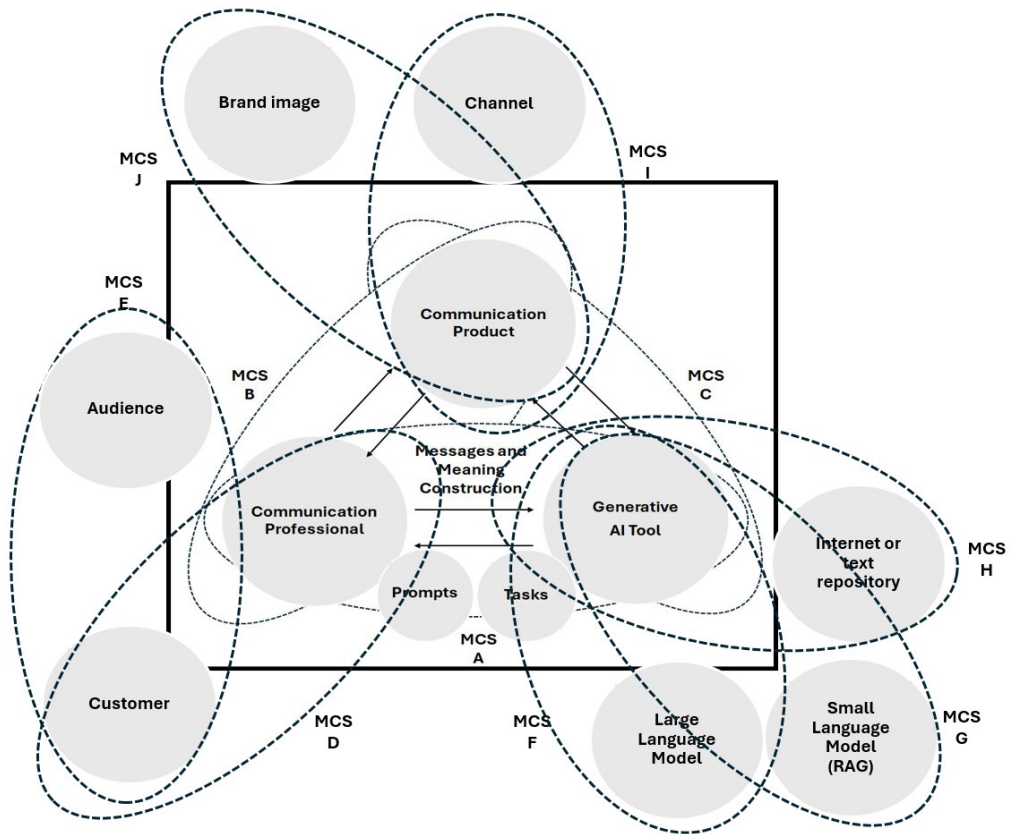


Figure 1: HMC Network Model for Communication Professionals

The HMC network model consists of an internal part (the inner square) and an external part (the outer square). The internal part includes the three meaning construction spaces in the internal network, while the external part includes the seven meaning construction spaces in the external network. The elliptical, dotted line shapes illustrate the meaning construction spaces (MCS) at play. The different meaning construction spaces in the study reported in this article are listed in Table 1.

Table 1: Meaning Construction Spaces in the HMC Network Model for Communication Professionals

MCS	Description
MCS A:	Meaning constructed between communication professional & GenAI tool
MCS B:	Meaning constructed between communication professional & communication product
MCS C:	Meaning constructed between GenAI tool & communication product
MCS D:	Meaning constructed between communication professional & customer

MCS	Description
MCS E:	Meaning constructed between the customer & audience
MCS F:	Meaning constructed between GenAI tool & Large Language Model (LLM)
MCS G:	Meaning constructed between GenAI tool & Small Language Model with Retrieval Augmented Generation (RAG)
MCS H:	Meaning constructed between GenAI tool & Internet/text repository
MCS I:	Meaning constructed between communication product & channel
MCS J:	Meaning constructed between communication product & brand image

The internal part of the HMC network model includes the communication professional, the GenAI tool, and the communication product (text, post, report, etc.). The arrows in the internal square indicate that messages flow from and to actors in the internal part. Meaning is created and constructed between the human communication professional, the GenAI tool, and the communication product in question. The internal part is characterised by three overall meaning construction spaces (Leroyer/Simonsen 2020: 186), referred to as MCS A, MCS B, and MCS C.

MCS A is the meaning construction space between the communication professional and the GenAI tool. This meaning construction space is characterised by a dyadic transfer of messages and encoding and decoding processes. The interplay between the human and the GenAI was discussed by Wilson/Daugherty (2020), who made the case for “collective intelligence”, and Mollick (2024), who uses the term “Co-Intelligence”. The actual interaction is referred to as prompting (the small circle called *Prompts* in Figure 1). Humans communicate with GenAI tools by means of prompt engineering, which seems to be a critical skill for communication professionals. To help them work effectively with GenAI tools in connection with especially text production, the structured prompting model was developed. The structured prompting model includes eight elements, as shown in Figure 2. The structured prompting model can be used as a source of inspiration for communication professionals when they prompt GenAI tools and can help them work strategically with prompting and help them remember the most important elements in an effective prompt.



Figure 2: Structured Prompting Model for Communication Professionals

Communication professionals increasingly also interact with GenAI tools with a conversational approach. A conversational prompting approach is necessary in connection with knowledge acquisition or idea generation. Consequently, a conversational prompting model was developed to help communication professionals work with a GenAI tool for idea generation or as a sparring partner, see Figure 3 below.

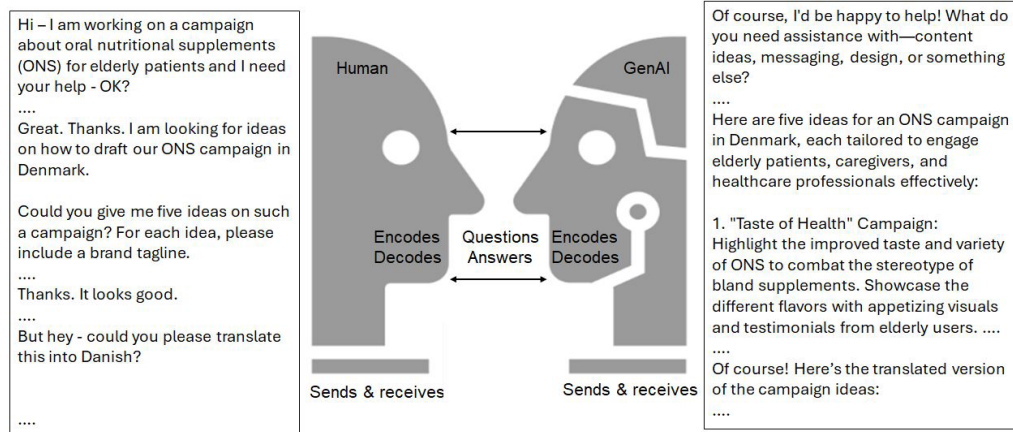


Figure 3: Conversational Prompting Model for Communication Professionals

The other small circle in MCS A is Tasks. In this context, communication professionals need to be able to characterise the type of tasks for which they use GenAI tools. Figure 4 offers a non-exhaustive overview of the different task-based communication practices of communication professionals (cf. also Simonsen 2024) and suggests six categories of situations in which GenAI tools can be used.

MCS B is the meaning construction space between the communication professional and the communication product. There is a special type of encoding, decoding, and interpretation between the two actors, and it is crucial for the communication professional to engage with the text, especially when it has been generated by a GenAI tool. In fact, the meaning construction here is crucial for the quality of the text, and it might even be argued that post-editing and quality assurance of GenAI-generated texts are very important disciplines in the AI era (Simonsen 2020, 2021, 2022).

MCS C is the meaning construction space between the GenAI tool and the communication product. This is also a special type of encoding, decoding, and interpretation by the two actors. Of course, the communication product is generated by the GenAI tool, and, for example, all changes and revisions made in the communication product by the communication professional flow back into the language model of the GenAI tool in question. Thus, the communication product itself becomes part of the GenAI tool.

In conclusion, the internal part of the HMC network model outlines the encoding, decoding, and meaning construction mechanisms taking place between the actors. However, to be able to analyse and discuss communication professionals' communication practices from an external perspective, we also need to include aspects such as audience, tone of voice, communicative function (inform, convince, etc.), and text types (social media posts, newsletters, press releases, etc.). For the purpose of this discussion, contextual information on the audience, tone of voice, communicative function etc. is part of the structured prompting model, see Figure 2.

<p style="text-align: center;"><b>Reception</b></p> <p>Use GenAI to summarize a text                      Use GenAI to generate list of concepts in text                      Use GenAI to analyse text                      Use GenAI to explain text                      Use GenAI to analyse data                      Use GenAI to explain data                      Use GenAI to compare two texts                      Use GenAI to compare two theoretical concepts                      ...</p>	<p style="text-align: center;"><b>Production</b></p> <p>Use GenAI to generate text                      Use GenAI to generate arguments for discussions                      Use GenAI to moderate discussions                      Use GenAI as a sparring partner                      Use GenAI as a writing tutor                      Use GenAI to find relevant references                      Use GenAI to change tone of voice or formality                      Use GenAI to adapt to another culture                      ...</p>
<p style="text-align: center;"><b>Translation</b></p> <p>Use GenAI to translate L1 text into L2                      Use GenAI to check L2 translation                      Use GenAI to explain L2 translation                      Use GenAI to change tone of voice                      Use GenAI to change formality level                      Use GenAI to adapt to another culture                      ...</p>	<p style="text-align: center;"><b>Proofreading</b></p> <p>Use GenAI to analyse text                      Use GenAI to proofread text                      Use GenAI to improve text                      Use GenAI to rewrite text                      ...</p>
<p style="text-align: center;"><b>Acquisition/Research</b></p> <p>Use GenAI to generate ideas                      Use GenAI to analyse data                      Use GenAI to brainstorm ideas or processes                      Use GenAI to suggest problem                      Use GenAI to suggest structure                      Use GenAI to suggest content                      Use GenAI to suggest methods                      Use GenAI to suggest data                      Use GenAI to find reference texts/companies                      ...</p>	<p style="text-align: center;"><b>Machine translation post-editing (MTPE)</b></p> <p>Use GenAI to analyse MT text                      Use GenAI to proofread MT text                      Use GenAI to improve MT text                      Use GenAI to rewrite MT text                      ...</p>

Figure 4: GenAI Task Model for Communication Professionals

The external perspective is also part of the HMC network model, which is the outer square encompassing the construction of meaning with external actors at different levels (Etzrodt et al. 2022: 440 f.). By including external actors and the relations between internal and external actors, the complexities of humans working with GenAI tools at different levels emerge.

MCS D is the meaning construction space between the communication professional and the customer. Here, special encoding, decoding, and meaning construction are taking place, and these complex activities influence both the communication product and the communication professional, as the customer might even demand lower prices because of the GenAI tool. MCS E is the meaning construction space between the customer and the audience and serves to illustrate that the reactions from the audience influence the customer, which in turn may influence how the customer interacts with the communication professional. Another important perspective in MCS D and E is the meaning construction of the communicative function of the text, the tone of voice, the rhetorical features of the text and discussions of which channels to use. These important communicative decisions influence almost all meaning construction spaces, especially the triangular cooperation between the communication professional, the GenAI tool and the communication product.

The three meaning construction spaces MCS F, MCS G, and MCS H on the right-hand side of Figure 1 are related to the meaning construction, encoding, decoding, and translation of meaning between the GenAI tool, the large language model (LLM), the small language

model with Retrieval Augmented Generation (RAG), and the Internet or the text repository in use if a RAG method is used. In this article, an LLM is described as a special AI model, which can recognise and generate text, among other tasks. An LLM is trained on huge sets of data including vast numbers of text examples. Different LLMs are used in tools like ChatGPT, Gemini, Copilot, Claude, DeepSeek and Grok. While an LLM is based on a huge general dataset, a RAG model is based on a specially selected dataset uploaded by the user. RAG stands for Retrieval Augmented Generation and is a special technology for enhancing the accuracy and reliability of GenAI tools typically based on quality-assured custom datasets uploaded by the user. The quality and size of the language model used are crucial for the quality of the output, which is also why extensive human post-editing of GenAI-generated texts might be required (Simonsen 2020, 2021, 2022).

The last two meaning construction spaces are MCS I and MCS J, which take their starting points in the communication product (campaign text, social media post, press release, etc.), the communication channel, and the brand image of the company or organisation. Brand image and the audience are closely related, but brand image encompasses the surrounding society, not only the audience. Finally, the communication channel itself also influences the communication product because of different channel conventions.

#### 4 Results

This section of the article presents and discusses the results from the quantitative parts of the survey, the thematically selected results from the qualitative parts of the survey, and the thematically selected results from the qualitative interview data. First, some general results from the closed, quantitative survey questions are outlined.

The respondents were first asked to provide their job titles. The three most typical job titles were “communication professional”, “communication expert”, and “communication consultant”, which correlates with the preferred job titles used by the respondents in the survey by *Kommunikation og Sprog* (2023: 5). When asked to what extent the respondents worked with languages in their position, a Likert scale from 1 to 5 (where 1 is very low and 5 is very high) was used. This question returned an average Likert scale score of 4.0, indicating that the 102 respondents use languages to “a high extent”. When asked about which languages they worked with, 100 % of the respondents said that they worked with Danish, 74.5 % with English, 7.1 % with German, and 2 % with French in their communication practices.

When asked about the extent to which the communication professionals already use GenAI, a Likert scale from 1 to 5 (where 1 is very low and 5 is very high) was also used. A surprisingly low average Likert score of 2.6 was observed, indicating that the communication professionals in this study has only worked with GenAI “to some extent”. These numbers contrast with the relatively high numbers reported by *Kommunikation og Sprog* (2023), with Danish participants, and *MyNewsDesk* (2023), with Scandinavian participants, which both report higher and more frequent uses of GenAI. These surveys were conducted early 2023 at a time when GenAI was hyped and many people started using it. However, on the basis of the interviews conducted in this survey, it might be argued that communication professionals have become somewhat more sceptical about the use of GenAI.

When asked about the extent to which GenAI impacts the position of communication professionals, an average Likert scale score of 2.4 was reached, which indicates that communication professionals have not yet been severely affected. When asked about the extent to which

GenAI impacts the quality of their work, an average Likert scale score of 2.9 was reached, which indicates that the respondents only see the quality of their work affected “to some extent”, which correlates with the reported use “to some extent”. When asked about the expected future of their positions as communication professionals, the respondents returned a slightly higher average Likert score of 3.7. This might indicate that even though the respondents do not seem to use GenAI to a very high extent, they expect that GenAI will impact their future significantly.

*4.1 How do communication professionals use GenAI in their communication practices?*

The data reveal several interesting insights in relation to RQ 1. First, insights from the survey are presented.

When asked an open-ended question about which tasks they solved by means of GenAI, a large number of tasks were listed by the respondents. Not surprisingly, the five most frequent tasks were “generate texts”, “review texts”, “translate texts”, “generate ideas”, and “analyse data”, which resemble the tasks reported on in Kommunikation og Sprog (2023), MyNewsDesk (2023), Simonsen (2023a and 2023b). However, the respondents also replied that they used GenAI to “find data”, “generate images”, “explain concepts”, “summarize texts”, and as a “sparing partner”. All tasks mentioned by the communication professionals in this study support the conclusions reached by Simonsen (2020, 2021, 2022).

Second, insights from the open-ended qualitative questions from the survey are outlined below. As mentioned above, a thematic coding scheme was developed, and the five themes defined for RQ 1 are shown in Table 2 together with selected examples from the qualitative comments.

*Table 2: Thematically selected statements of relevance for RQ1*

<b>RQ 1: How do communication professionals use GenAI in their communication practices?</b>	
<b>Theme</b>	<b>Selected statements from survey</b>
Translation	“I use AI for translating both short and long texts, especially when time is limited.” “It’s a great tool for making quick translations, but it still requires a manual review and proofreading.” “AI makes it easier to translate complex texts, but it’s important to ensure that nuances are preserved.”
Idea generation	“I use it to beat ‘the curse of the blank page syndrome’ – to generate ideas, which I in fact do not use, but which inspire me to have better ideas.” “I use GenAI for research purposes, that is, collection and structuring of background information, which I use and build on.” “Generative AI has become an integral part of my work, from planning to production.” “It’s a tool that complements my own creativity and efficiency.”

Theme	Selected statements from survey
Text production	<p>“I use AI both for small tasks such as email drafts and for larger projects such as strategic presentations.”</p> <p>“I often start with AI to create a first draft of blog posts or articles.”</p> <p>“Text production with AI makes it easier to generate variations of content for social media.”</p> <p>“I use GenAI to generate texts, e-mails, texts for LinkedIn, translations, and ideas for posts and texts.”</p>
Proofreading	<p>“I use AI for proofreading, especially to check for grammatical errors and redundancy.”</p> <p>“It’s useful for detecting spelling mistakes, but it can’t always understand the context.”</p> <p>“AI helps to quality assure texts to make them look more professional.”</p>
Practical use/ other	<p>“I use it as a sparring partner. I often ask GenAI about an idea / something that I have written to check whether it understands it the same way that I want it to be understood.”</p> <p>“I use GenAI to reduce the length of texts, rewrite texts (for example from a boring professional text to an interesting press release), to sparring on texts, generate ideas, generate agendas and programs, generate ideas for branding and campaigns, draft project plans, translate from Danish to English and for entertainment. “</p>

The results indicate that communication professionals are quite innovative when it comes to using GenAI, and the results contribute to our understanding of the encoding and decoding between the communication professional and the GenAI tool (MCS A). Many respondents indicate that they use GenAI as a “sparring partner” and for other tasks. The respondents also indicate that they use GenAI to generate almost all text types, and that they use GenAI for idea generation and research purposes. In conclusion, the results indicate that GenAI is used for both “producing” and “strategic” purposes. In other words, communication professionals who primarily write texts use GenAI for text generation (“producing”), and communication professionals who primarily advise on communication strategies etc. use GenAI to draft creatives or storylines (“strategic”). The results also offer an empirically based overview of how communication professionals interact with GenAI and describe the many different text types generated by communication professionals using GenAI. The structured prompting model and the conversational prompting model suggested and shown in Figures 2 and 3 may help us understand how to work effectively with GenAI tools.

Finally, the following selected statements from the eight interviews add additional insight into the use of GenAI by communication professionals. Interview person 1, who is a campaign manager at a Danish newspaper, works with native advertising and states that “I am a newbie ... In fact, the only thing I use ChatGPT for is translating texts. That is what I use it for.” She continues: “I work in relation-building, and here ChatGPT cannot be used at all – because it is about human relations.” Interview person 4 is a key account manager at an Edtech company and states: “I work in the educational industry, and I only use ChatGPT as a sparring partner. I think that we are somewhat conservative when using GenAI tools. We are concerned about

data security. Therefore, I see it as a sparring partner. I would never use what it generates – because I want to use my own words and thoughts.” The last two statements are categorised under the theme “Practical use/other” and adds a more critical perspective on the use of GenAI.

Interview person 5 has designed and created his own GPT and is very competent in using GenAI. He said: “I uploaded a few, but very good documents and slides – and I tested it. I tested and tested and found some errors and then I uploaded better slides. In total four files and many slides. I have tested my own GPT vis-a-vis ChatGPT 4.0 and my own is much, much better, because it contains context and situation.” When asked about the quality of the output, interview person 5 said: “The quality was really good. Once I asked it to come up with an activity plan and it was really good. And it also contains the right details. At some point I uploaded some theory, but I stopped doing that, because the GPT started to generate too much irrelevant and fuzzy information. So, I deleted that content. There is so much potential in this technology.” The statement above by interview person 5 belongs to the theme “Idea generation” and demonstrates that some communication professionals have already started building their own GPTs with their own curated data. Finally, interview person 8 said: “I actually think that prompts are completely similar to briefing creative teams on what to do. I mean – you really need to give them background, context, objectives, and expectations – and you have to present all the steps - so I use the same approach when prompting.” This statement underlines the need for using structured prompting when working with GenAI tools and the suggested prompting models in Figures 2 and 3 may help communication professionals work with GenAI tools.

#### *4.2 Do communication professionals think they have sufficient knowledge and skills to use GenAI in their communication practices?*

The results for RQ 2, which aimed to analyse and discuss whether communication professionals have sufficient knowledge and skills to use GenAI, indicate that a large majority of the respondents seem to lack both knowledge and skills to be able to use GenAI optimally. Again, the overall framework of the HMC network model helps us understand what the communication professionals need. First, insights from the closed, quantitative survey questions are outlined.

When asked to what extent they had received structured teaching or instruction on how to use GenAI, an overwhelmingly large proportion of the respondents (82 %) said that they had not been taught how to work with GenAI. Furthermore, those who had in fact received instruction on how to use GenAI reported that the type of instruction received was cursory and inadequate. A similar trend is seen in MyNewsDesk (2024), where one statement reads: “... almost two-thirds (63 %) say they or their department are still in the explorative phase of understanding different generative AI tools and solutions ...”, which seems to indicate that there is a large unmet training need in most organisations. The need for training is elevated to a strategic level by another expert in MyNewsDesk (2024), who writes “Generative AI is not going away. Employers will demand that their workforce use AI, and you cannot possibly compete with somebody using AI smartly and intelligently to support their work. So, if you want to stay in the business, you must eventually accept and adjust to it.” In other words, GenAI and how communication professionals use it are critical business factors and training in how to use GenAI is perhaps the easiest and most profitable way to improve working with a GenAI tool.

Second, insights from the open-ended qualitative survey questions are outlined below. Again, the thematic coding scheme was used. Table 3 below shows the five themes defined for RQ 2, and, for each theme, selected examples from the qualitative comments are listed.

Table 3: Thematically selected statements of relevance for RQ 2

<b>RQ 2: Do communication professionals think they have sufficient knowledge and skills to use GenAI in their communication practices?</b>	
<b>Theme</b>	<b>Selected statements from survey</b>
Lack of training	<p>“I haven’t received any training, so I’m trying to figure it out on my own.”</p> <p>“Most of my knowledge about AI comes from YouTube videos and online articles.”</p> <p>“It’s a challenge to understand the technology when you have no guidance.”</p> <p>“I have had a short introduction, but not a real course.”</p> <p>“I need to learn much more about how to use the GenAI tool to obtain the results I want.”</p>
Cursory training	<p>“We had a short introduction to AI at work, but it wasn’t in-depth.”</p> <p>“I was given a workshop on AI, but I still feel I lack practical experience.”</p> <p>“The courses I’ve taken have been useful, but mostly focused on the basics.”</p>
Limited knowledge	<p>“I do not know how to communicate with our GenAI. I would love to learn how.”</p> <p>“I know a little about how to use AI for specific tasks, but not enough about the technical aspects.”</p> <p>“My experience with AI is limited to a few experiments with tools like ChatGPT.”</p> <p>“I don’t feel confident enough to implement AI in large parts of my work.”</p>
Limited experience	<p>“I’ve only experimented with AI, but not used it for serious tasks.”</p> <p>“I lack practical experience to use AI more effectively.”</p>
Need for structured learning	<p>“I would like a course that covers both the possibilities and limitations.”</p> <p>“Structured training would help make AI more accessible to all of us.”</p> <p>“I need a deeper understanding of AI in order to use it strategically.”</p> <p>“I see endless possibilities when using GenAI in my work, but there are also limitations because we have not been trained to use it and how we are allowed to use it. It would be nice to have clear guidelines, and I think all companies should prepare guidelines.”</p>

The results selected from the qualitative comments of the survey listed in Table 3 indicate that communication professionals lack knowledge of GenAI and training in how to use GenAI tools. The results also indicate that it is not only about learning how to use new technology,

but also about preparing value-adding guidelines to help employees work within the limits of the company in question and initiating major changes in processes.

Finally, the following statements from the eight interviews add additional insight into the competence level of communication professionals. Interview person 1 said that “I only use it for translation – so on a scale from 1 to 5 – I would say that my competence profile when it comes to using GenAI is a small 2”. When asked about prompting skills she continues: “To be absolutely frank, the first time I heard about prompting was when you told me about it last week – so I would rate myself as 1 on a scale from 1 to 5.” A different insight appears in the interview with interview person 2, who said: “I think that I am above average – so perhaps a 4 on a scale from 1 to 5.” When asked about her competence level in using GenAI tools, interview person 2 said that “I have taught myself how to prompt, but it is definitely learning by doing. I have never received structured instruction, but I have participated in webinars free of charge.” These statements by interview persons 1 and 2 are categorised under the themes “Lack of training” and “Limited knowledge” and seem to demonstrate that communication professionals need structured training in how to use GenAI. The HMC network model may help us understand that what they need to learn takes place within MCS A, MCS B and MCS C.

Interview persons 3, 4, 5, 6 and 8 also supplied statements that related to the themes “Lack of training” and “Limited knowledge”. When asked about her GenAI competences on a scale from 1 to 5, interview person 3 stated that “I think that I would be a 3 on a scale from 1 to 5 – I use GenAI – but I also experience that I do not know how to write a working prompt.” When asked whether she had received any sort of structured instruction or education in how to use GenAI she said that “No I have not – but I watch a lot of TikTok videos.” Interview person 4 expressed something similar, stating that “I think that I would be a 3 on a scale from 1 to 5” and adding that “I have not received any training or instruction on how to work with GenAI – I guess I just started using it.”

In contrast to this, communication executives seem to argue that their competences in using GenAI tools are quite high. When asked about competences, interview person 5, who is Head of Sales in a large Scandinavian publishing house, said: “I think that I am a 5 because I have worked with ChatGPT for quite some time. I have also created my own GPT. It took me around 1.5 hours and it works really well.” A similar statement came from interview person 6, who is a CEO at a large communication company. He said: “I would say that I am a 4 on a scale from 1 to 5.” Finally, interview person 8, who is a CEO of an international communication company said: “I have used ChatGPT for the last year and use it daily. And right now, I attend an online course on how to use GenAI.”

Again, the HMC network model, especially MCS A, MCS B and MCS C, may help us understand the complexities of working with a GenAI tool and the three decision support models on structured prompting, conversational prompting and GenAI tasks may also help us understand what type of training communication professionals need.

#### *4.3 What type of help do communication professionals need in their communication practices?*

RQ 3 focused on analysing and discussing what type of help communication professionals need in their communication practices. First, insights from the open-ended qualitative questions from the survey are outlined, drawing on the developed thematic coding scheme. Table 4

below shows the five themes defined for RQ 3 and lists selected examples from the qualitative comments.

Table 4: Thematically selected statements of relevance for RQ 3

<b>RQ 3: What type of help do communication professionals need in their communication practices?</b>	
<b>Theme</b>	<b>Selected statements from survey</b>
Models on GenAI and communication professionals	<p>“I want a better understanding of how AI can help with specific communication tasks.”</p> <p>“We lack information on how AI can be integrated into our existing workflows.”</p> <p>“AI should be more customised to the needs we have in the communication industry.”</p>
Security & GDPR	<p>“I am concerned about data security, especially in relation to sensitive information.”</p> <p>“How can we ensure that AI is GDPR compliant when we use it for text production?”</p> <p>“It’s important that we understand the risks associated with sharing data with AI systems.”</p> <p>“I work in the financial sector, so I am very cautious when using GenAI.”</p>
Organisation-specific guidelines	<p>“Right now, there is a big focus on how we can use GenAI, and AI policies are being drafted while we speak.”</p> <p>“I work in a governmental institution and we have not yet received guidelines for the use of AI and are basically not allowed to use AI at all (although many do).”</p> <p>“I see endless possibilities when using GenAI in my work, but there are also limitations because we have not been trained to use it and how we are allowed to use it. It would be nice to have clear guidelines, and I think all companies should prepare guidelines.”</p> <p>“We need a strict AI policy, and we need to approve all the tools that we use.”</p>
Quality assurance	<p>“We really need methods to fact-check output.”</p> <p>“I think that we need processes and tests, including human quality checks.”</p>
Guidelines on ethics	<p>“We need ethical guidelines and guidelines on declaration of sources.”</p> <p>“AI raises many ethical questions, especially about attribution and copyright.”</p> <p>“How do we ensure that AI does not unconsciously reinforce existing prejudices?”</p> <p>“We need to be aware of how AI affects the credibility of our communication products.”</p>

The insights indicate that communication professionals need models or frameworks on how to work with GenAI, and that they need guidelines on AI use, confidentiality, and GDPR. The insights seem to indicate that communication professionals need guidelines on how not to compromise confidential and sensitive data when interacting with GenAI tools, and MCS E, MCS F, MCS G and MCS H in Figure 1 may help professional communicators understand and construct the realities of working with GenAI tools. Finally, the communication professionals also indicate that they need more management support and more strategic change management efforts. In other words, it is not only about learning how to use new technology, but also about preparing value-adding organisation-specific guidelines to help employees work within the limits of the company in question.

Finally, the following selected statements from the eight interviews add additional knowledge in relation to RQ 3. The interview data support the findings listed above in Table 4. Interview person 1, for example, clearly states what she needs. She says that “I would say that I need clear instructions on how to prompt. I could also use guidelines on copyright, sources, references, and so on.” When asked the same question, interview person 5 said:

I think that I need a prompting framework of some sort that could help me understand what ChatGPT needs in the prompt and I also think that I need a model to build on prompts already executed. I think that I know how to prompt – but on a scale from 1 to 5 I might be a 3 – and it is not just about writing a prompt – we need to be accurate and precise – and we need to describe in detail what we want.

Towards the end of the interview, she also added that “Maybe we need some sort of declaration model – to indicate when we use GenAI and for what.” These statements fall under the themes “Organisation-specific guidelines” and “Quality assurance” and indicate that communication professionals need more practical help when prompting.

## 5 Discussion

This study investigated the practices of communication professionals “in an AI era” (Gates 2023) and analysed how communication professionals use GenAI (RQ 1), whether communication professionals have sufficient knowledge and skills to use GenAI (RQ 2), and what type of help communication professionals need when working with GenAI (RQ 3). The thematically selected results were outlined and discussed above and the HMC network model and the three decision support tools on structured prompting, conversational prompting and GenAI tasks were used to analyse the meaning constructions at play.

With regard to RQ 1, an overwhelming majority of the respondents said that they used GenAI, but that they did not use GenAI in a structured way or in specific situations. When asked what types of tasks the respondents use GenAI for, the five most frequent tasks were “generate texts”, “review texts”, “translate texts”, “generate ideas”, and “analyse data”, which are similar to findings in *Kommunikation og Sprog* (2023), *MyNewsDesk* (2023), *Simonsen* (2023a and 2023b). The interviews furthermore showed that many communication professionals use GenAI as a sparring partner. As demonstrated above, many respondents and interviewees indicate that meaning construction between the actors is quite difficult.

Communication professionals seem to struggle with the encoding of what they want to achieve by means of the GenAI tool, and the data analysed show that communication pro-

professionals find it difficult to prompt and ensure quality of the output. Furthermore, the actual communication process between the human user and the GenAI tool seems to be difficult for many users, and the data show that communication professionals need tools with which they can communicate with the GenAI tool. This complex situation can be analysed and constructed by means of the HMC network model. It is evident that a lot of meaning construction is taking place in the internal part of the HMC network model (MCS A, MCS B and MCS C). Some interviewees even mention the meaning construction between the communication professional and the customer, that is, MCS D, and some of the more seasoned users of GenAI tools discuss the underlying design of the GenAI tool in question, that is, they construct meaning in MCS F, MCS G and MCS H.

With regard to RQ 2, an overwhelming majority of the respondents and interviewees said that they were not competent in using GenAI. A total of 82 % of the respondents said that they have not been taught how to work with GenAI. Many interviewees also said that they had to teach themselves how to use GenAI tools by for example watching TikTok videos. This somewhat detached approach by managements is thought-provoking because it illustrates that the communication profession neither seems to have understood the magnitude and importance of the GenAI disruption nor seems to have understood how to go about this and use GenAI strategically (Humlum/Vestergaard 2024). Again, the HMC network model is relevant because it helps us understand the complexity and feeling of uncertainty felt by many communication professionals. When analysing the results through the HMC network model lens, it dawns again that the primary meaning construction takes place in especially the three internal meaning construction spaces, MCS A, MCS B, and MCS C. The meaning constructions taking place in these spaces indicate what type of training is needed for communication professionals. The meaning constructions, illustrated by means of the many statements by both respondents and interviewees, indicate that what communication professionals need is hands-on training in how GenAI tools work, how to communicate with GenAI tools, and how to ensure the output quality.

With regard to RQ 3, an overwhelming majority of the respondents and interviewees stated that they need knowledge about how GenAI tools work, how they can be used, and how to prompt GenAI tools. The interviews showed that the communication professionals also need different guidelines on GDPR, data security and quality assurance. Again, when analysing the meaning of what was said by the interviewees and elevating the insights from the data to a higher cognitive level by means of the HMC network model, it is argued that the two developed prompt models situated in the internal part of the HMC network model meet some of the needs described. Finally, it is argued that the HMC network model itself can help communication professionals navigate in their new role as partners in a collaborative working relationship with a GenAI tool and can help them construct and understand their own uncertainty about how to encode and decode messages to and from the GenAI tool. Furthermore, there seems to be a large need for active management support and value-adding, organisation-specific guidelines on how to use GenAI.

The data show that the respondents and the interviewees express uncertainty, frustration, fear, and a feeling of alienation, and it is argued that this special cooperation between the communication professional and the GenAI tool will reshape the way we see communication practices in the future. The data analysed and discussed above seem to suggest that we need additional frameworks and business models for communication professionals using GenAI tools. Communication professionals might be challenged on for example price and deadline

for their services or asked to provide GDPR compliance status or GenAI accreditation for their services. However, based on the data analysed in this study, it is argued that GenAI in fact is a catalyst for many communication professionals.

Finally, when reflecting on the limitations of the study it is clear that it might have been useful to observe and record how communication professionals use and prompt GenAI tools in real use situations. Furthermore, it might have been better if the interviewees had been directly asked about what type of training they needed. All that might have improved the quality of the data significantly and revealed new insights into the training needs of communication professionals.

## 6 Conclusions

GenAI is transforming the field of communication, presenting both opportunities and challenges for communication professionals. This study examined how communication professionals use GenAI, the extent of their competencies, and their needs when integrating GenAI into their workflows. The findings highlight several critical questions.

First, while GenAI tools are widely recognised and used by communication professionals, they do not yet seem to be fully integrated or utilised systematically in communication practices. Many communication professionals use GenAI as a sparring partner for idea generation, drafting, and review, but their engagement with these tools remains exploratory. This indicates a significant potential for further integration of GenAI into routine practices in the communication field.

Second, the study revealed a widespread lack of formal training and structured instruction on how to use GenAI effectively. Most respondents and interviewees expressed a need for education on prompting, quality assurance of output, and understanding the underlying mechanisms of GenAI. This competence gap underscores the necessity for targeted training and organisational support.

Third, the data revealed that communication professionals require tools, models, and frameworks to optimise their use of GenAI. This includes prompting frameworks and ethical guidelines to address important concerns about data security, references, and quality. Such resources can help bridge the gap between the potential of GenAI and its practical application.

Finally, the findings suggest that the integration of GenAI is a very complex process that involves meaning construction across multiple dimensions, as illustrated by the HMC network model. Effective GenAI use requires communication professionals to navigate interactions between humans, machines, and communication outputs, as well as external actors such as customers and audiences. This complexity calls for a multidimensional approach to understanding and utilizing the huge potential of GenAI in communication.

In conclusion, while GenAI offers immense potential to enhance productivity and creativity, its successful adoption requires significant investments in training, the development of decision-support tools, and the establishment of robust operational guidelines. Clearly, there is a large need for additional research in this area.

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# Integrating Artificial Intelligence in the Higher Education of Technical Writers and Technical Translators

*Marion Wittkowsky & Ralph Krüger*

**Abstract** Compared to translation and interpreting studies, which have already had a long-standing tradition, technical writing studies only emerged in the mid-1990s. At that time, so-called translator workbenches, which include several support functions for translators, became state-of-the-art tools. In addition, machine translation (MT) systems were put into operation and led to a change in translator's daily activities. For example, additional tasks like pre-editing the original texts and post-editing the machine-translated versions have become routine. In addition to actual translation competence, knowledge about how to evaluate and optimise texts, etc., became necessary. Although the original texts to be translated by translators are normally written by technical writers and although the two professions share many common features (Schubert 2007: 103), translators often know very little about the actual work processes of technical writers and vice versa. Now, with the rapidly growing potential influence of generative artificial intelligence (AI) systems, which are mostly in the form of large language models (LLMs), both professions have to come to terms with the fact that many of their daily activities can now potentially be (semi-)automated through these technologies. These tasks include, among other things, information research, text analysis, text production, correction/editing, terminology work, and of course translation. This article argues for the integration of generative AI in the higher education of both technical writers and technical translators, since it is highly likely that LLMs and other generative AI competences will not only be desired but explicitly requested by potential future employers and clients. Therefore, this article will discuss several examples of what and how universities could teach aspiring technical writers and translators so that they become experts in language-oriented AI.

**Keywords** artificial intelligence, digital literacies, higher education, large language models, technical translation, technical writing

## 1 Introduction

This article discusses potential additions to the curricula of translation and specialised communications programmes (at BA and MA levels) that students and graduates of these programmes may require in a professional world where high-performing language-oriented AI technologies in the form of large language models have recently emerged. The article argues that universities should strive to educate their students so that they become experts not only in technical writing and translation, but also in reading, evaluating, and preparing data for natural language processing (NLP) through relevant software systems. With regard to NLP skills, technical writers nowadays usually learn some basics of text technology and information

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data usage for authoring and content management systems, whereas translation studies have traditionally focused more on language and communication skills. For example, even when working in machine-aided human translation (MAHT) processes, translators often take on the role of an end user and do not intervene in more computational linguistics-oriented tasks such as defining rules for rule-based MT or other NLP systems, or training and fine-tuning machine learning (ML)-based systems such as neural machine translation (NMT) systems or LLMs. To be prepared for future tasks in the field of (multilingual) specialised communication, both technical writers and technical translators also need to acquire proficiency in performing cross-professional tasks (Wittkowsky 2022: 273 f., see also Angelone's [2022: 65] discussion of *adaptive expertise*). To get an idea of what these tasks are, section 2 categorises and situates them within the multilingual specialised communication process.

The need for a reorientation in multilingual communication studies did not only emerge with the appearance of LLMs in 2022. It had already been obvious since 2016, when NMT systems started to be implemented and used in professional translation environments. Both NMT systems as well as current LLMs can be implemented in human-aided machine translation (HAMT) workflows in the overall multilingual communication process. In such a HAMT scenario, the translations are generated automatically and language experts perform all tasks except for the translation itself, for example pre-editing, post-editing and other system interactions. From relevant surveys such as the European Language Industry Survey (ELIS), we know that language professionals, here technical writers and technical translators in particular, are already using related software systems such as authoring systems, terminology databases, controlled-language checkers (CLCs), etc. in their daily work (ELIS Research 2024: 36–39). Also, within university programmes a wide range of software tools is taught and a certain degree of digital literacy is developed in their students (ELIS Research 2024: 35–38).

When we talk about AI systems in the field of multilingual specialised communication, we mostly refer to LLMs such as OpenAI's GPT models or Anthropic's Claude models.<sup>1</sup> Even if LLMs are similar in their underlying architecture to former narrow AI systems (e.g., NMT systems such as DeepL), they need to be handled in different ways (cf. the discussion in section 3). A basic knowledge of how these systems work as well as of their capabilities and their limitations will allow language experts to confidently handle these systems when they are incorporated in multilingual specialised communications processes. The systems can be seen as new actors within the overall process, and LLMs are becoming an additional everyday device for technical writers and technical translators.

Section 2 takes a look at how AI system integration in the international technical communication process may be achieved. We then look at the new tasks and interfaces for technical writers and technical translators that have emerged in parallel with the introduction of current AI technologies. In section 3, the DataLit<sup>MT</sup> project (cf. Krüger/Hackenbuchner 2022) based at TH Köln is introduced. In this project, didactic resources have been developed that combine *data literacy* and *machine translation literacy* for students in BA and MA programmes for translation and special communication in order to reflect the ongoing digitalisation and datafication in the language industry. The section also discusses how data and MT literacy have recently been integrated into the more comprehensive concept of domain-specific AI literacy, which may be required by technical writers and translators working in AI-assisted workflows. Prior to the conclusion in section 5, section 4 illustrates example scenarios where AI skills and

<sup>1</sup> Cf. <https://openai.com> and <https://claude.ai>.

competence development have been implemented in selected BA and MA courses in International Technical Communication studies at Flensburg University of Applied Sciences. In these scenarios, students should develop an understanding of the challenges associated with current AI technologies, not only in the processing of natural language but also in the preparation of data for specific usage scenarios, for example with regard to information design.

## 2 Interfaces between the work of technical writers and technical translators in specialised communication and potentials for AI assistance

One of the main reasons for the existence of various points of contact between the work of technical writers and technical translators in the overall field of specialised communication is that both professions communicate content mainly via the medium of natural language. In particular, the dimension of multilinguality extends not only to different national languages but also to different language varieties, such as plain language, easy language or subtitles for inclusion purposes. The generative AI systems that are in the focus of this article are LLMs which, even if they nowadays are able to process and generate pictures, sounds and videos (multimodal LLMs), were originally designed for language or text processing (unimodal LLMs).

Looking at a *simplified multilingual specialised communications process* (Wittkowsky 2022: 94), we can define the main language-oriented tasks of technical writers and technical translators as *information research*, *text production*, *text translation*, and *text correction/editing* (cf. Göpferich 2008b). At this point, we intentionally ignore other software systems besides LLMs that may be used to assist or to complete these tasks.

The following section is divided into three sub-sections: initially, a short overview of the theoretical modelling of *text production and text translation processes*, both established fields of research, is given in order to identify similarities and differences and to determine points of contact between the two processes.<sup>2</sup> Then, we will zoom in on the *text correction/editing* stage, which is a very important and at the same time labour-intensive stage in the overall writing/translation process. The section concludes with a discussion of the *information research* stage. Although the overall process usually starts with this research phase, we address text production/translation and text correction/editing first since these stages lie at the very heart of the (multilingual) specialised communication process.

### 2.1 Text production and translation processes in technical communication

As mentioned above, a simplified model of the multilingual specialised communication process assumes that a text is produced in one language in order to establish an original version of a text.<sup>3</sup> AI systems may be incorporated in the entire process in order to produce text. This can be the first version of a given content, i. e., the original text, or a translation generated by an AI system based on this text. One might think that it would be easier to ask an AI system to write separate texts in all languages required instead of performing translations into these

<sup>2</sup> For a comprehensive overview of specialised translation in the field of technical communication as well as a comparison of the tasks and knowledge repositories of technical writers and technical translators, cf. Byrne (2006: 1–45).

<sup>3</sup> This also is required by the Regulation (EU) 2023/1230 of the European Parliament and of the Council on machinery (2023).

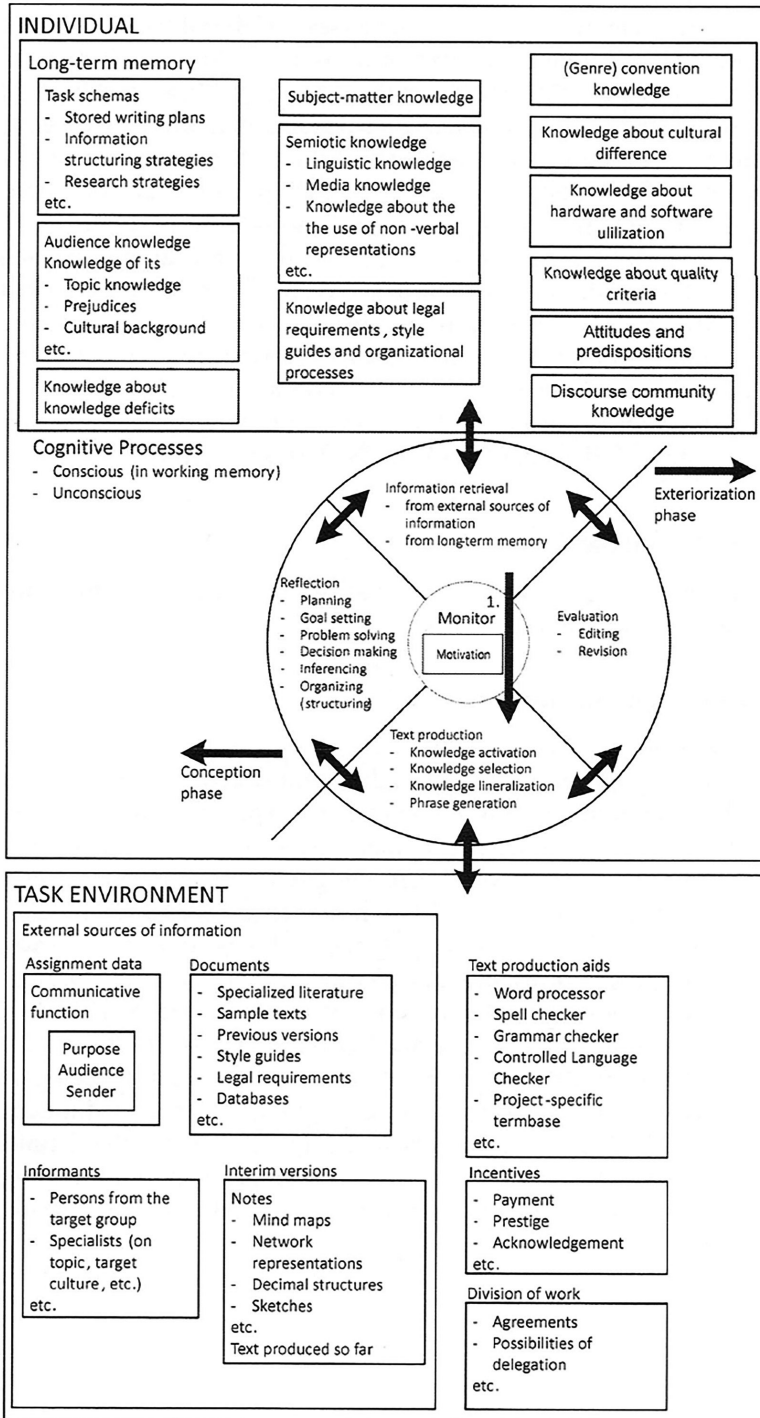


Figure 1: Instruction-oriented writing process model, Göpferich (2015: 129)

languages. However, it seems questionable whether this approach is actually feasible since it seems to offer less control over text content than machine-translating one source text into different languages. Thus, it seems necessary for the original text being translated if versions in other languages are required.

In order to identify the similarities and differences between the tasks of text production and translation, we take a quick glance at some relevant models, such as the *instruction-oriented writing process model* by Göpferich (2002/2008a), the *specialised translation process* by Heidrich (2016) and the *draft model of the situated technical writer* by Krüger (2016). The survey of these models will focus on those aspects with particular relevance to the present discussion.

The Göpferich model depicted in Figure 1 is divided into two sections: The individual in the upper section refers to the technical writer, where a distinction is made between long-term memory activities and cognitive processes. The task environment in the lower section com-

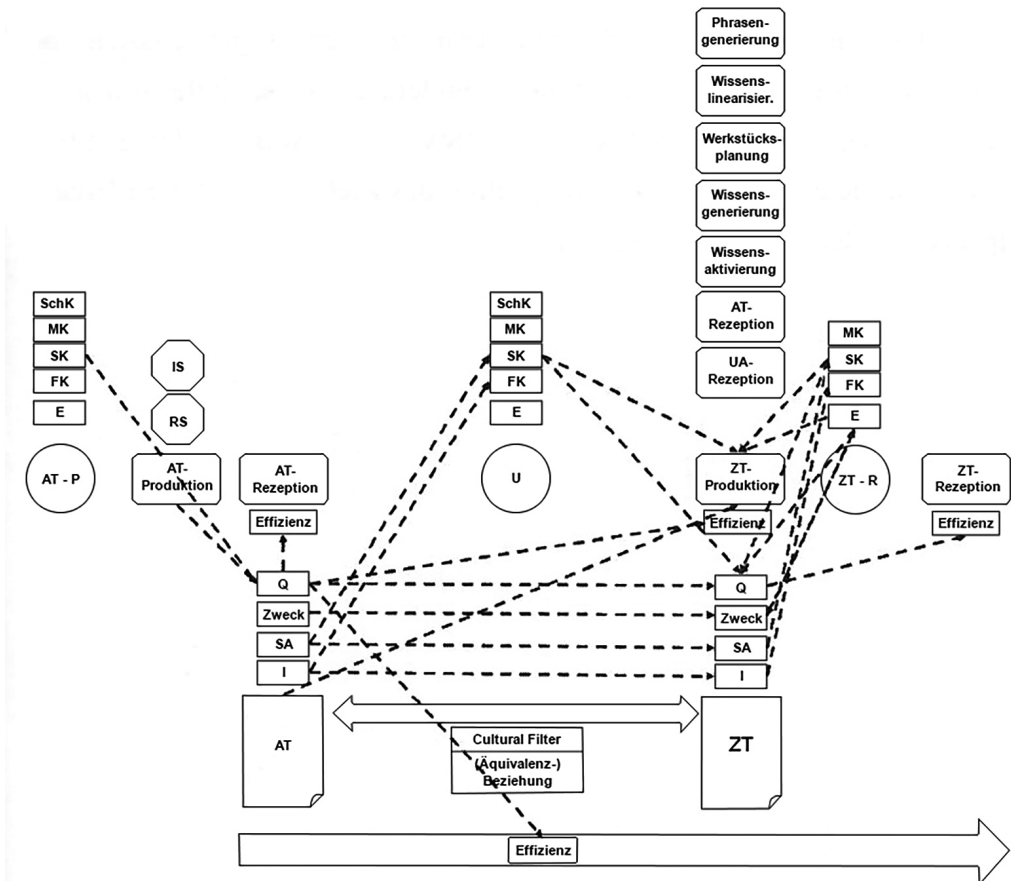


Figure 2: Specialised translation process with external parameters (Heidrich 2016: 237) (Ü = translator, SchK = writing competence, MK = media competence, SK = language competence, FK = subject area competence, E = settings and expectations, IS = information structuring, RS = controlled language, ÜA = translation brief, ZT-R = target text recipient; own translation)

prises external sources of information and tools that are used to support writers in their daily work (nowadays, these tools could comprise AI systems as discussed in this article). The *individual* section links all types of knowledge the technical writers (ought to) possess for a writing project, including the cognitive processes the individual runs through, either consciously or unconsciously, when working on this project (Göpferich 2002/2008a: 250).

Figure 2 shows Heidrich's model of the *specialised translation process* with a focus on the *translator's knowledge* which comprises language, media, subject area and writing competences and the *external parameters* (Heidrich 2016: 227–236). Similar to Göpferich's *task environment*, Heidrich lists, for example, settings and expectations, information structuring, translation briefs, and target text recipients as additional external influences.

Krüger's *draft model of the situated technical writer* shown in Figure 3 is based on the Cologne model of the situated LSP (language for special purposes) translator (Krüger 2016: 36) and divides the *process chain of specialised communication* (Schubert 2007: 132–135) into two main phases, the *create* and the *organize/use* phase. In this model, the artefact groups in the upper part as well as the cooperation partners in the different phases can roughly be equated with the task environment in Göpferich's model. The sub-tasks of the create phase partially resemble the cognitive processes and the elements situated in the head of the technical writer (competence, macro strategy, frames) are somewhat similar to the long-term memory in the Göpferich model.

With the rapid advancement of language-oriented AI, the roles of technical translators and technical writers are now even more similar in terms of cognitive prerequisites for their everyday tasks. Here, we divide both processes, the writing and the translation process, into two processing areas, the *internal area* and the *external area*. The internal processing area comprises all abilities listed in Göpferich's model under the *individual* as well as the *competences* listed in Heidrich's and Krüger's *create* phase from a process perspective. The external processing area includes all external parameters that contain the specifications for individual projects as well as the working environment in which such writing or translation projects takes place. In the current AI era, users need to know how to incorporate AI systems in the whole process chain, which may need to be combined with traditional software systems, such as text editors, terminology databases, translation memory systems etc., to achieve optimum results. Also, the proper use of supplementary documentation, language rules and other specifications as well as the expectations of the customers play an important role for technical writers and translators in their everyday work.

## 2.2 Potentials for AI assistance

Today, we expect AI technologies such as LLMs to have access to all the basic information pertaining to the competences that form part of the *internal processing area* mentioned above. In order to prepare an LLM to perform the desired tasks at a high level of quality while at the same time taking into account the actual role it has to take on – here, writer or translator – a so-called *prompt* has to be defined, which should contain detailed information on the tasks the model is supposed to perform. In addition, all necessary information from the *external area* should be made available to the LLM. As discussed above, technical writers and translators perform many tasks that are common to both professions in (multilingual) specialised communication. An LLM prompt can be considered the steering instrument that contains the instructions for the model. Ideally, it should be written either by technical writers or technical

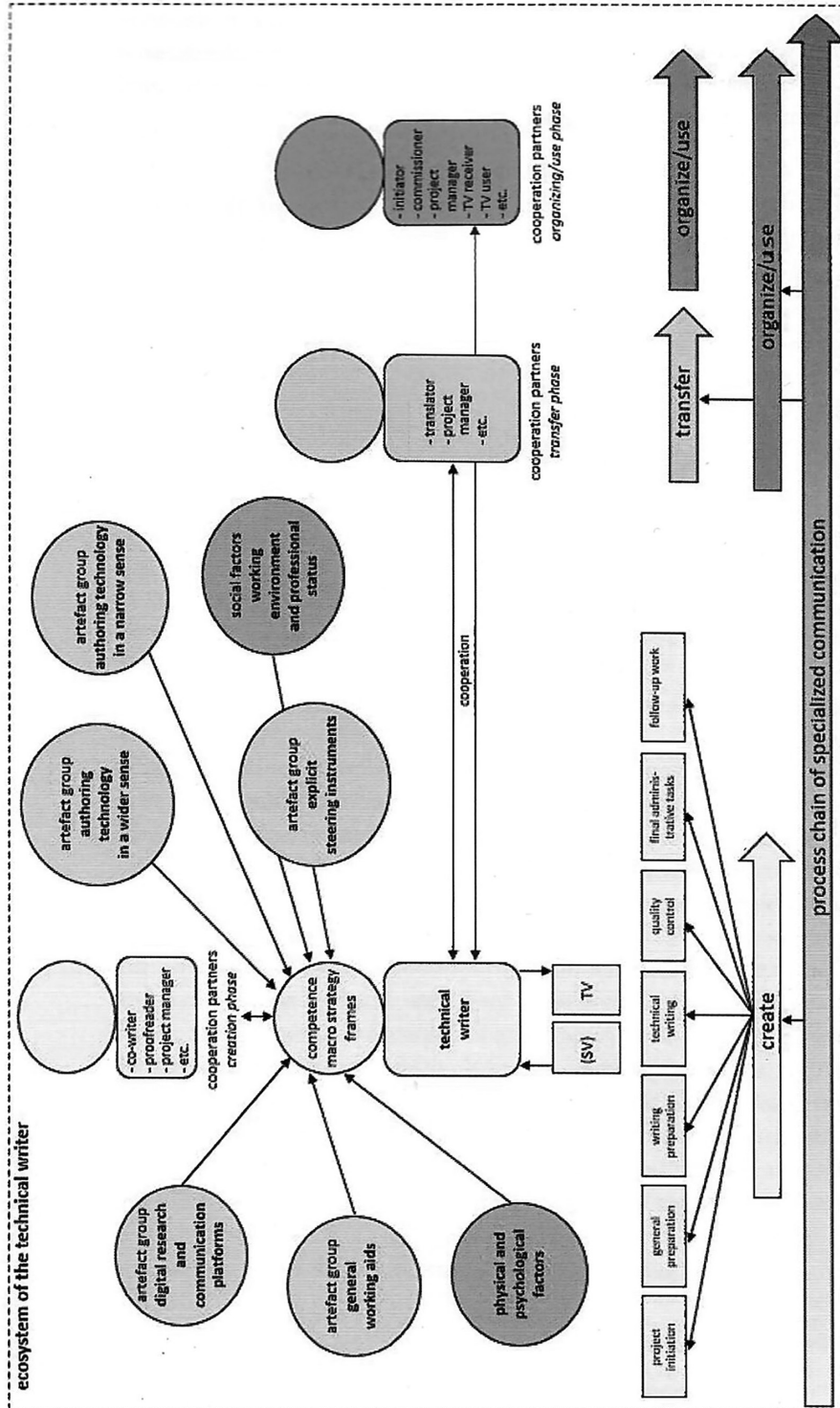


Figure 3: A draft model of the situated technical writer (Krüger 2016: 36)

translators, depending on the content to be created,<sup>4</sup> and it should consist of a minimum set of specifications as outlined in List 1 below:

- the role that the system has to take on: technical writer or technical translator,
- the language or language pair used,
- the type of information product to be developed,
- the target group(s) for the text,
- an exact delineation with regard to the content to be written,
- an exact delineation with regard to the information design, i.e. micro and macro structure,
- the rules that have to be applied when producing or translating content as the case may be,
- the steps that have to be followed by the AI system during text production or translation in the correct chronological order, and
- additional files, content or similar information to be considered during the writing or translation processes.

*List 1: Minimum set of specifications*

The list above is intended to serve as a starting point for prompting LLMs for particular tasks. It should be evident that the instructions provided to an LLM are very similar to the instructions to be found in style guides or writing guidelines for technical writers and technical translators. Moreover, prompt creators need to be aware of the following information outlined in List 2:

- the basic functions of AI systems, particularly of LLMs,
- how to conceptualise LLMs as distinctive target groups (for which prompts are written) and how to interact with them adequately,
- the explicit setup of the overall (multilingual) communication process in which the LLM is used,
- which additional information, for example terminology, is necessary and where to find it.

*List 2: Information necessary for prompt creation*

When language professionals like technical writers or technical translators use LLMs, they should already have substantial knowledge with regard to the points contained in List 1. On top of this, they should learn to use several AI systems competently and become aware of ongoing changes in the system landscapes, which is covered by the AI literacy concept discussed in section 3.<sup>5</sup>

Having discussed the technical writing and translation professions and how AI, especially LLMs, might be embedded in work processes, the following sub-section takes a deeper look at the text correction and editing phases of the writing/translation process.

<sup>4</sup> See the example scenario discussed in section 4.

<sup>5</sup> At this point, some important issues, such as the quality of legacy data and all other resources provided for the AI systems, have not been considered, since these are general aspects and a prerequisite for every successful writing and translation process and are therefore excluded here.

### 2.3 Text correction/editing

The skills required for text correction/editing are very similar to those required in the text production and translation phases. However, as mentioned before, when it comes to evaluating the accuracy of the intended meaning of a written statement, evaluators have to be very well educated and experienced, because although the AI system output often is grammatically correct and stylistically adequate, some errors cannot be avoided by the systems. It has to be taken into account, however, that post-editors may tend to be overly critical of the quality of MT output, since it is their objective to improve output quality (Hansen-Schirra/Schaeffer/Nitzke 2017: 166), which may lead them to over-edit the output.

Evaluating a text does not only mean deciding whether it is factually correct. The evaluation of a natural language text, whether it was written by a machine or by a human, is a very demanding task due to the distinct properties of natural languages, as outlined by Wittkowsky (2014: 101):

Natural languages have certain properties that may cause misunderstandings among the recipients regarding the intended message sent by the sender. One of the main problems with natural languages is ambiguities.

Natural languages allow expressing one and the same meaning using different syntactic constructions or lexical units. The quotation above was part of a paper that examined how students of multilingual specialised communication courses should be prepared for working in a human-aided machine translation (HAMT) process.<sup>6</sup> While human translators cannot intervene during the actual MT process, here they can, for example, control the language data beforehand by pre-editing the original text (cf. Wittkowsky 2014, 2022). Text production rules (these are part of the external parameters discussed in sub-section 2.1) can also be included in an LLM prompt to perform an automatic pre-editing of original texts prior to an AI translation or to check whether these texts exhibit a good machine translatability. Implementing such rules within the process may also help to improve the learning effect of an AI system. An essential prerequisite for obtaining high-quality translation results is that the original texts are grammatically correct, use consistent terminology and, in terms of style, address the right target group and adhere to the genre conventions of the specific information product. Seewald-Heeg (2017) considers the quality validation of the original text to be a mandatory task for post-editors in order to decide whether including a post-editing step is worth the effort (Seewald-Heeg 2017: 159).

Evaluation of MT output can be performed by automatic evaluation metrics such as COMET (Crosslingual Optimized Metric for Evaluation of Translation; cf. Rei et al. 2020); however, students also need to know how a manual evaluation is carried out (as covered by the Linguistic MT Literacy dimension of the Professional MT Literacy Framework discussed in section 3).

The method of evaluating and correcting or post-editing the AI system output depends, among other things, on how the AI system is integrated in the entire translation process. AI systems can be used as standalone systems, or they can be implemented upstream or downstream of other systems, such as controlled-language checkers or translation memory systems. So-called hybrid systems or system combinations allow for optimised translation results.

<sup>6</sup> The MT system discussed in the paper was a rule-based system.

However, first of all, students should learn how to read and further process the raw output of an AI system.

Thus, in this article the focus is on standalone AI systems, with or without a glossary function.<sup>7</sup> Wrong terminology can be easily replaced, also with the help of an AI system, provided that terminology databases exist for all languages involved. This, for example, may include a simple search-and-replace step for wrong terminology, as proposed by Grizzo (2017: 180). So-called negative lists, which contain forbidden terminology, are also very helpful to search for and replace wrong terminology.

After the post-editing step, a final proofreading step is required (Seewald-Heeg 2017: 157). In addition to validating the correctness of the text, the overall quality also needs to be checked.<sup>8</sup>

Further mandatory skills for technical writing or translation students involve the following (List 3):

- |   |
|---|
| <ul style="list-style-type: none"> <li>– general knowledge in contrastive linguistics and controlled languages,<sup>9</sup></li> <li>– knowledge about evaluation methods with regard to different quality levels,</li> <li>– knowledge about proofreading standards and annotation methods for correction or post-editing purposes.</li> </ul> |
|---|

*List 3: Mandatory skills for technical writing or translation students*

#### 2.4 Information research

Information research is a typical task of technical writers and includes content- as well as language-related research. This task involves many different types of sub-tasks and is mandatory when writing a high-quality technical documentation for a product. Technical writers are supplied with different types of information, which may include technical product information by the developers, internal company writing guidelines, external standards, information concerning the subject area as well as company-specific terminology (cf. the external parameters in the models discussed in section 2). Moreover, expert interviews are a reliable method to ensure that the information gathered is correct (Schubert 2007: 83 f.). In an ideal world, an almost similar scenario applies to technical translators: they will be provided with an original text of ideally high quality, have access to style guides as well as to specific terminology pertaining to particular subject areas and corporate languages. In case of additional questions, technical writers and translators may expand their knowledge by performing additional research and combining the research results with their existing knowledge in the respective subject area. Prior to the emergence of LLMs, this additional research had mainly been conducted by consulting experts or by searching the intranet of a company or the internet. Nowadays, AI systems can provide information in mere seconds.

However, the quality of the information produced by AI systems depends on various aspects. One aspect is the ability of the person querying the LLM to formulate an adequate

<sup>7</sup> The usage of correct corporate terminology is a prerequisite and should be standard practice in order to achieve the best possible results.

<sup>8</sup> See working step 5 in section 4.

<sup>9</sup> Standard writing guidelines are supplied by tekomp, European Association for Technical Communication – tekomp Europe e.V. ([www.tekomp.eu](http://www.tekomp.eu)), for example.

prompt. Moreover, AI systems not only generate authoritative sounding answers; they also often provide additional information that was not requested or which could be deemed superfluous. They can assist in gathering missing information as well as confirming or challenging preconceptions. This means that AI systems can be very helpful for the research work and may also provide company-specific data, provided they have been trained or fine-tuned on such data. For doing research, querying an AI system may be more efficient than searching the internet.

When using an AI system, technical writers and technical translators take on the role of the customer and have to prompt the system with the information mentioned at the beginning of this section. When LLMs receive more detailed information, they tend to produce high-quality output that better matches the request.

The tasks discussed in this section are basic everyday tasks for technical writers and technical translators. Before presenting an example-based AI working scenario in a student project in section 4, we introduce in section 3 the DataLit<sup>MT</sup> project, in which didactic resources have been developed that combine *data literacy* and *machine translation literacy* for students in BA and MA programmes for translation and (multilingual) specialised communication. We also illustrate how data and MT literacy have recently been integrated into the more comprehensive concept of domain-specific *AI literacy*, which can be operationalised in the context of technical writing and translation.

### 3 Machine translation literacy, data literacy and artificial intelligence literacy for technical writers and translators

The ongoing digitalisation and datafication of the language industry – which, as discussed above, has recently been accelerated by high-performing AI technologies such as NMT and LLMs – has led to the emergence of a range of digital literacies that have become relevant to the various stakeholders of the modern language industry, among them technical writers and technical translators. Focusing particularly on the interface between two such digital literacies, i. e. *data literacy* and *machine translation literacy*, the DataLit<sup>MT</sup> project based at TH Köln (cf. Krüger/Hackenbuchner 2022) set out to develop didactic resources for teaching data literacy in its translation-specific form of MT literacy to students of BA and MA programmes in translation and specialised communication. To do so, the project developed a professional MT literacy framework,<sup>10</sup> which distributes overall professional MT literacy over the five dimensions of *technical MT literacy*, *linguistic MT literacy*, *economic MT literacy*, *societal MT literacy* and *cognitive MT literacy* (Krüger 2022: 250). This framework was then linked to the DataLit<sup>MT</sup> framework, an MT-specific data literacy framework,<sup>11</sup> which depicts the typical data lifecycle in an MT project. This framework distributes overall MT-specific data literacy over the five dimensions of *data context*, *data planning*, *data collection/production*, *data evaluation* and *data use*. The full interface between the two frameworks and their individual (sub)dimensions is discussed in detail in Krüger (2023: 306–310). Based on this interface, a

<sup>10</sup> The concept is defined as “the full range of MT-related competences professional translators (and other language professionals) may require in order to participate successfully in the various phases of the MT-assisted professional translation process” (Krüger 2022: 249).

<sup>11</sup> Data literacy is “the ability to collect, manage, evaluate, and apply data, in a critical manner” (Ridsdale et al. 2015: 11).

competence matrix was developed, where the DataLit<sup>MT</sup> framework provided the individual (sub)competences to be taught and the professional MT literacy framework provided the specific application contexts that guided the creation of the corresponding learning resources. For example, *data preparation* as a subdimension of the data collection/production dimension of the DataLit<sup>MT</sup> framework describes a range of competences that are relevant in an MT training pipeline as a subdimension of technical MT literacy as part of the professional MT literacy framework. This application context guided the development of a learning resource which aids students in preparing data for training their own NMT model (along with further training resources focused on NMT model training, MT quality evaluation, etc.). The full range of DataLit<sup>MT</sup> learning resources, which are provided as open educational resources under a Creative Commons license (CC BY-SA 4.0), is available on the DataLit<sup>MT</sup> project website.<sup>12</sup>

As discussed above, recent LLMs such as OpenAI's GPT models extend to a considerable degree the range of workflows and tasks in the language industry that can potentially be (semi-)automated via high-performing language AI technologies. At the same time, these general-purpose LLMs require a different handling than previous narrow AI systems such as dedicated NMT systems (DeepL etc.). This requires an extended set of digital literacies on the part of language industry stakeholders, which go beyond 'traditional' data and MT literacy as conceptualised by DataLit<sup>MT</sup> and which could be subsumed under the broader concept of *artificial intelligence literacy*.<sup>13</sup> Against this backdrop, Krüger (2024) proposes an AI literacy framework for translation, interpreting and specialised communication, in which domain-specific AI literacy is distributed over the five dimensions of *technical foundations*, *domain-specific performance*, *interaction*, *implementation* and *ethical/societal aspects* (Krüger 2024: 15–21). For example, with regard to technical writing, the domain-specific performance of current LLMs potentially covers autonomous text production, optimisation of text quality or intralingual translation, e. g., by transforming design engineering notes into draft operating manuals (which would then have to be *post-edited* by human technical writing experts), as illustrated by the practical example in section 4.

At the same time, the AI literacy framework covers new modes of human-AI interaction such as prompting LLMs for MT tasks (see Lists 1 and 2 above). This 'conversational MT' approach only emerged with the invention of chatbot-style LLM systems such as ChatGPT in late 2022 / early 2023 and was hence not covered by DataLit<sup>MT</sup>'s professional MT literacy framework. Currently, competence levels and descriptors for the individual (sub)dimensions of the AI literacy framework are being developed, which are intended to lay the groundwork for the didactic operationalisation of the framework in the spirit of DataLit<sup>MT</sup>. The learning resources to be developed in this context will hopefully contribute to developing domain-specific AI literacy in the higher education of technical writers and technical translators.

The frameworks surveyed above are very detailed and illustrate the complexity of the topic at hand. The next section shows an example-based AI working scenario for students that can be used as a starting point for related types of work. The extent to which students of multilingual specialised communication dive into the AI technology will depend, among other things,

<sup>12</sup> <https://itmk.github.io/The-DataLitMT-Project/> (30.11.2024).

<sup>13</sup> The concept describes "a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace" (Long/Magerko 2020: 1).

on the semester the students are in as well as on the type of programme the students participate in (BA or MA, writing or translating, scientific or practice-oriented, etc.).

#### 4 Examples of how to integrate AI in translation and specialised communication courses

In this section, we present a working scenario that is intended to resemble the daily practice of technical writers and technical translators. Over the years it might be observed that students will become more engaged in a class project when it is set up as a real-world project. However, if for any reason a real-world project with a real customer is not possible, artificial scenarios mirroring real-world conditions can also be developed. Suitable technical devices, for example, household appliances are often familiar to students. They are well documented, and instruction manuals as well as other types of documentation are often freely available on the internet so that they can be used as long as no opt-out has been declared by the copyright owner.

##### *Preliminary Considerations*

In the present example, the technical device to be used is an espresso machine, for which a complete and correct instruction manual already exists. The information product requested is a *quick reference guide* for one of the main functions, here the *descaling* function. In addition, the new quick reference guide needs to be translated into one or more target languages. The knowledge about the content that is required to write the quick reference guide can be obtained by reading the existing manual as well as other documents that can be found in the internet. The espresso machine itself is not available to students, so that they cannot directly test the functions to be described on the device. The students are supposed to use a freely available LLM and to decide on the tasks for which they feel that the LLM may be useful (in line with the *domain-specific performance* dimension of the AI literacy framework discussed in section 3). Moreover, students are asked to document their work as well as their findings and to evaluate the results. Consequently, a positive side-effect should be that they learn to combine their practical work with academic examination and research methods. The main working steps included in this scenario are shown in Figure 4.



Figure 4: Working steps in an AI-assisted technical writing and translation scenario for students

Apart from the actual *prompt writing* step, each of the steps is already part of the everyday tasks of technical writers and translators and requires knowledge of many small tasks that are typical within the overall field of specialised (multilingual) communication as discussed in section 2.

##### *Working step 1: Information research*

The existing instruction manual of the espresso machine and possible further documentation (so-called legacy data) can be used to write the new quick reference guide. In order to incorpo-

rate an LLM into the information research phase, students first need to feed the LLM with the original instruction manual and other related materials.<sup>14</sup> The way the documentation is made available to the LLM depends on the inherent functions of the LLM used. Some systems have the ability to process files; others can only access information that is pasted into their chat interface. In order to obtain the information required to write the short reference guide, students are supposed to ask the AI system to collect all information that is connected to the *descaling* function from the manual as well as from other documents the LLM has been provided with. For example, a prompt in this case could be: “In the documentation provided, search for all the information that is required to generate a quick reference guide on the topic of *Descaling*. List descriptions as well as instructions and put together complete sections as well as small text blocks that are related to *descaling*.” Traditionally, technical writers are the people who perform this type of work, because they are the ones who create content. However, if this step is part of creating documentation in other languages, it could also be performed by translators. The result of this information research can then be used for the following steps.

#### *Working step 2: Writing rules and style guide creation*

Prior to writing the prompt, writing rules on how to write short technical instructions should be defined, since quick reference guides follow other rules than full operating manuals, not only with regard to content but also with regard to information design, which comprises the structuring and language usage (cf. Riegel 2001). This step might also be performed by consulting an AI system and having the system write the rules. What is important here is that the person querying the LLM needs to have extensive knowledge about writing rules in general as well as basic knowledge about quick reference guides. Depending on whether another language version is produced by means of translation or by means of writing another original text in that language, the main actors in this step can be both technical writers or technical translators.<sup>15</sup> If an AI system is asked for support, the resulting rules should be checked again by a human expert before moving to the next step.

#### *Working step 3: Writing a prompt for the LLM*

After the research work is complete and writing rules have been defined, the data gathered can be provided to the LLM together with a prompt that contains detailed instructions on how to use the materials and write the new document “Quick reference guide for *descaling* your espresso machine”. To be able to write a prompt, students need to know what kind of information the LLM requires so that it can generate a correct quick reference guide with regard to content and language and that follows the style expected and defined for quick reference guides. Prompting forms part of the *interaction* dimension of the *AI literacy framework* discussed in section 3. As far as the original language version is concerned, the tasks linked to this working step are mainly performed by technical writers. If the LLM is requested to generate output in another language, then the same task, i. e., writing a prompt, has to be performed for the other language as well. When the prompt is complete, it can be used to instruct the LLM to generate the output. Next is the post-editing step, in which errors or other discrepancies in the LLM output have to be corrected.

<sup>14</sup> In this scenario it is not desired that the LLM searches the internet to gather information.

<sup>15</sup> For non-natives, guides with rules on how to write English in technical documentation are available, for example, the *tekomp* (2017) guidelines on English for non-native writers.

*Working step 4: Post-editing*

In this scenario, the post-editing step focuses on linguistic correctness, based on the linguistic and stylistic rules defined/specified beforehand. This step should be performed by technical writers or technical translators depending on the language version of the texts. It is also possible to employ controlled-language checkers, which may also partly employ AI for error correction. For example, CLCs are able to recognise the *genus verbi* and to propose the usage of active or passive voice depending on the context. The post-edited version is then used as a basis for the work performed in step 5.

*Working step 5: Final quality check of the quick reference guide*

With regard to content, this check can only be performed by comparing the quick reference guide with the original manual, since the espresso machine is not available to validate whether the steps in the guide adhere to the correct sequence or use the correct terminology. The comparison can either be done with the aid of an AI system or manually. A comparison that is performed by an AI system of course needs to be checked again by humans afterwards. An evaluation of the quick reference guide with regard to, e.g., plausibility or comprehensibility, can be done by using qualitative usability checks.

*Summary of the project*

Text production as well as translation are performed by making use of the LLM as much as possible. The students' tasks are to perform information research, to instruct the LLM via adequate prompting and to check and validate the LLM output. The validation involves checking content as well as structure and linguistic quality of the different language versions. There has been a slight shift towards an even more complex usage of traditional and new software systems. The overall working tasks for technical writers and technical translators have changed slightly; however, the amount of knowledge required when working in the field of AI-assisted specialised multilingual communication becomes more extensive, an impression supported by the digital literacy frameworks discussed in section 3.

## 5 Conclusion

The main premise of this paper was that both technical writers and technical translators should be educated in working with AI systems, mainly LLMs. AI systems may be integrated in a company's system landscape and make use of more or less company-internal information and documentation. This means that, depending on the level of integration, AI systems have at their disposal more or less suitable and targeted information. The systems can exist as a stand-alone system without any integration, or they can be combined with other language processing systems in different ways. A maximum degree of integration is reached when AI systems are fully incorporated in the overall process, which means that they have access to other information-rich systems in such a way that they are enabled to execute their deep learning processes based on the data repositories of a company. A prerequisite for providing high-quality data is that the company's data has been well maintained (see, for example, the data literacy discussion in section 3).

What does this mean for the education of technical writers and technical translators? The educational approaches and the main working fields of the two professions are getting closer (cf. Wittkowsky 2022). There is a strong need for higher education in multilingual specialised

communication that covers the traditional elements of the discipline and additionally focuses on various components of digital literacies in the language industry as discussed in section 3. And there are the other competences, in addition to digital ones, that should be integrated into higher education in multilingual specialised communication, such as operational, management and soft skills.<sup>16</sup> The development of these new competences and the adjustment to these new requirements should happen today and be accompanied by fundamental as well as broad research activities.

Good language and writing skills are still of very high importance for technical writers and technical translators and may become even more relevant in the future. It is very important to be able to write adequate prompts so that AI systems will be able to perform the requested tasks with as much accuracy as possible. Technical writers and translators also require organisational as well as medium-related competences, since each project has its own rules and follows its own procedures and methodologies that have to be taken into account while planning the project. In order to qualify for technical writing and translation tasks in settings where highly standardized language use is required, knowledge on topics like controlled language and information structuring also becomes more important. Even if the AI systems themselves could be used to write guidelines, checklists etc., human language experts need to be able to ensure that the final product conforms to the required quality level.

What are the challenges and risks and which new elements need to be introduced into modern technical writer and translator education? Multilingual specialised communication brings together many different actors that form a heterogenous group with partly overlapping approaches to language content. The collected know-how of technical translators and technical writers forms a knowledge repository to which both professions should have access so that they know about the consequences of their activities (Wittkowsky 2022: 273 f.). The digital literacy frameworks discussed in section 3 pave the way for a technology-oriented higher education of technical writers and technical translators, which is necessary to cope with any future tasks and identify risks when working with AI systems. Consequently, there is a need to change the learning outcomes of students and adapt them to the new requirements of an increasingly AI-saturated language industry.

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<sup>16</sup> See, for example, the Personal and Interpersonal as well as the Service Provision categories of the current European Master's in Translation Competence Framework ([https://commission.europa.eu/system/files/2022-11/emt\\_competence\\_fw\\_k\\_2022\\_en.pdf](https://commission.europa.eu/system/files/2022-11/emt_competence_fw_k_2022_en.pdf)) (24.2.2025).

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# Maschinelle und menschliche Übersetzung im Vergleich am Beispiel des Entwurfs des ersten ungarischen Zivilgesetzbuches (Deutsch – Slowakisch)<sup>1</sup>

*Peter Gergel, Olga Wrede, Daša Munková & Lucia Benková*

**Abstract** Neural machine translation enables fast and automated translation of large volumes of text, which, in many cases, can be more efficient than translation by human translators. However, for specific communication purposes, the quality of machine translation remains a challenge. This also applies to legal communication, as legal texts require a high level of accuracy, precision and expertise that cannot always be provided by machine translation systems. This article compares the translations of an inheritance law text from German into Slovak produced by four translation tools (DeepL, Google Translate, eTranslation, ChatGPT) with human translation. The study focusses on the accuracy of the translation of the relevant inheritance law terminology and the possible causes of incorrect and therefore unacceptable translation solutions. The results of the study show that, despite the progress made, neural machine translation is not yet sufficiently mature for a translation in accordance with legal norms. For this purpose we have chosen a legal-historical text (the draft of the first Hungarian Civil Code), whose translation into Slovak, compared to machine translations, could perhaps show new ways to be able to translate larger amounts of legal-historical texts and their terminological inventory later on in order to make the translation work more effective.

**Keywords** German-Slovak translation, human translation, inheritance law, legal terminology, machine translation, AI

## 1 Einleitung

Die Entwicklung Künstlicher Intelligenz und damit verbundener Sprachmodelle greift maßgeblich auch in die Sphäre der Translation ein, sodass den professionellen Übersetzer:innen heute diverse ausgereifte Übersetzungstechnologien zur Verfügung stehen. Diese ermöglichen

<sup>1</sup> Die Studie ist im Rahmen der Projekte APVV-23-0192 Kontrastívny výskum kolokácií v slovenských a nemeckých dedičskoprávnych textoch (Kontrastive Untersuchung von Kollokationen in slowakischen und deutschen Texten des Erbrechts) und APVV-18-0473 Klasifikačný model chybovosti strojového prekladu: Krok k objektívnejšiemu hodnoteniu kvality prekladu (Ein Klassifizierungsmodell der Fehlerquote maschineller Übersetzung: Ein Schritt zu einer objektiveren Bewertung der Übersetzungsqualität) entstanden, die von der Agentur zur Unterstützung der Forschung und Entwicklung (APVV) finanziell gefördert werden.

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ihnen u. a., Übersetzungsprozesse im Allgemeinen effektiver und schneller zu gestalten (Arbeits- und Zeitaufwand vs. steigendes Übersetzungsvolumen).

Die Frage danach, ob der Einsatz der maschinellen Übersetzung (MT – engl. *machine translation*) in der heutigen Übersetzungsbranche seinen festen Bestand hat, hat sich mittlerweile erübrigt. Das ständig wachsende Volumen an Übersetzungsaufträgen, die möglichst in kurzer Zeit und kostengünstig erledigt werden sollen, die Vielfalt an Sprachkombinationen und letztendlich auch wirtschaftliche Interessen sowie allem voran die unaufhaltsame Entwicklung der Künstlichen Intelligenz und damit maschineller Übersetzungssysteme lassen keinen Zweifel daran aufkommen, dass die maschinelle Übersetzung zu einem nicht mehr wegzudenkenden Bestandteil der globalisierten Welt geworden ist.

Dass jedoch jede Münze zwei Seiten hat, darf an dieser Stelle nicht geleugnet werden. Auch wenn grundsätzliche Bedenken am Einsatz der maschinellen Übersetzung kaum mehr von Relevanz sind, so wird doch nach wie vor über die Qualität der mittels maschineller Übersetzung angefertigten Translate diskutiert. Diskussionen in puncto qualitativ hochwertiger Übersetzung flammen dabei im Wesentlichen unter professionellen Übersetzer:innen auf. Aufgrund ihrer Ausbildung, Fachkenntnis, langjährigen Erfahrung und der Kenntnis der Praxisanforderungen können diese profund beurteilen, inwieweit die maschinell erstellte Übersetzung den Qualitätskriterien im Hinblick auf Verständlichkeit und Sprachfluss, terminologische Korrektheit und Konsistenz, stilistische und textsortenspezifische Gepflogenheiten usw. entspricht (vgl. Munková/Vaňko 2017, Way 2018, Bánik et al. 2019, Dall-Zaunna/Kurz 2019 u. v. a.).

Unbestritten bleibt jedoch, dass maschinelle Übersetzungen in letzter Zeit vor allem dank neuronaler Netzwerke enorme Fortschritte gemacht haben. Gerade aber hier versteckt sich auch die eigentliche, oft nicht erkannte bzw. nicht ganz ernst genommene Gefahr der maschinellen Übersetzung. So kann eine maschinell erstellte Übersetzung einem Laien beinahe „perfekt“ vorkommen, da sie sprachlich verständlich und flüssig ist und keine gravierenden grammatischen Fehler aufweist.<sup>2</sup> Andererseits aber kann sie durchaus schwerwiegende terminologische Fehler, fehlerhafte oder irreführende Deutungen und Bezüge aufweisen, die dem Laien verborgen bleiben (vgl. Porsiel 2020: 6). Für spezielle Zwecke (beispielsweise rechtliche oder medizinische) ist so eine Übersetzung nicht nur unzureichend und inakzeptabel, sondern birgt in sich die Gefahr eventueller Personen- und Sachschäden und kann schließlich irreversible Folgen nach sich ziehen. Diese Meinung vertritt u. a. auch Schmalz (2019: 195):

Was ein Übersetzungsprogramm wirklich leisten muss, hängt stark vom Zweck ab. Wird eine automatische Übersetzung im kommerziellen, politischen oder juristischen Umfeld genutzt, ist es für die Außendarstellung eines Unternehmens wünschenswert oder rechtlich sogar nötig, dass die Übersetzung vollständig korrekt ist.

Zudem begegnen manche der Übersetzer:innen maschinell angefertigten Übersetzungen nach wie vor mit einer gewissen Skepsis. Diese ergibt sich u. U. neben einer eventuell nicht

<sup>2</sup> Laut Läubli (2021: 41) ergaben verschiedene Blindtests, dass Laien neuronale maschinelle Übersetzungen häufig als besser beurteilen, als dies professionelle Humanübersetzer:innen tun. Die Gründe dafür mögen einerseits darin liegen, dass professionelle Übersetzer:innen besser in der Lage sind, aufgrund ihrer Ausbildung und jahrelangen Erfahrung Ungenauigkeiten in Übersetzungen zu erkennen. Andererseits haben Laien gegenüber maschinell erstellten Übersetzungen eine neutralere Haltung, da sich die Technologie nicht auf ihren Lebensunterhalt auswirkt.

ausreichenden bzw. nicht vorhandenen Erfahrung mit dem Einsatz maschineller Übersetzungssysteme in eigener Übersetzungspraxis auch aus einer etwas irreführenden Vorstellung davon, wie die maschinelle Übersetzung letztendlich funktioniert (vgl. Guerberof/Moorkens 2019). Aussagekräftige und durchaus interessante Daten brachte in diesem Zusammenhang in puncto Technologiekompetenz von Übersetzer:innen eine breit angelegte Untersuchung von Djovčoš/Šveda (2017), die unter slowakischen Übersetzer:innen und Dolmetscher:innen durchgeführt wurde. Die häufigsten Antworten auf die Frage, warum man keine CAT-Tools verwende, gingen dahin, dass man die Art des Textes („kreative“ Texte, Literatur, amtliche Dokumente) für zu spezifisch hielt, dass man über nicht hinreichend gute technische Kompetenzen verfüge (fehlende Ausbildung, unzureichende Vorbereitung während des Studiums auf die Nutzung entsprechender Tools) oder dass mit der Verwendung von derartigen Tools der Preis für Übersetzungen nach unten nivelliert werde (vgl. Djovčoš/Šveda 2017: 81). Es ist jedoch zu betonen, dass angesichts des aktuellen Technologiestands und der zunehmenden Bereitschaft, neue Technologien in der Übersetzungs- und Dolmetschpraxis einzusetzen, die Ergebnisse einer solchen Untersuchung durchaus anders ausfallen könnten.

Um die Nutzungseffektivität von Übersetzungssystemen zu gewährleisten, bedarf es vorrangig eines Verständnisses dessen, was diese Tools können, wo ihre Grenzen sind und wie diese gehandhabt werden, um das erwünschte Ergebnis (eine qualitativ hochwertige Übersetzung) zu erzielen (vgl. Bowker/Ciro 2019).

Wie gut (im qualitativen Sinne) eine maschinell angefertigte Übersetzung gelingt, hängt allerdings von einer Vielzahl an Faktoren ab. Gemeint sind damit etwa die Qualität des Ausgangstextes, die Art der Textsorte (Werbetext vs. Bedienungsanleitung vs. Rechtstext), das Sprachenpaar (Englisch/Deutsch vs. Deutsch/Slowakisch), die dem Übersetzungsauftrag angemessene Übersetzungsstrategie (verfremdende vs. einbürgernde Übersetzung) und nicht zuletzt auch das eingesetzte Übersetzungssystem (Google Translate vs. DeepL vs. eTranslation vs. ChatGPT u. a.). Obgleich der Einsatz maschineller Übersetzung in der Übersetzungsindustrie und die Verbesserung ihrer Qualität immer stärker und unaufhaltsamer wird, ist die maschinelle Übersetzung, wie bereits erwähnt, bei Weitem noch nicht fehlerfrei und bedarf u. U. eines menschlichen Eingriffs. Manche der Meinungen gehen sogar so weit, dass bezweifelt wird, ob eine zuverlässig fehlerfreie, maschinelle Übersetzung überhaupt möglich sein wird, da einem Computer die für die kontextsensitive Übersetzung nötige Alltagserfahrung fehlt (vgl. Schmalz 2019). Daher ist der völlige Ersatz des Menschen (des:der Übersetzer:in) durch die Maschine vorerst nicht zu fürchten.<sup>3</sup> Umso mehr sollte die Maschine nicht als in einem Konkurrenzverhältnis zum Menschen stehend betrachtet („Maschine statt Mensch“), sondern das Verhältnis als gleichwertige Partnerschaft gewertet werden („Mensch und Maschine“). Durch diese neue Perspektive kann ein Gleichgewicht zwischen den Fähigkeiten der Maschine und denen der menschlichen Übersetzer:innen erreicht werden (vgl. Vigier-Moreno/Pérez-Macías 2022: 76). In der Praxis zeigt sich nach Huehls/Groth (2019: 178) sogar, dass die Rolle des Menschen noch wichtiger geworden ist, wenn es darum geht, die Qualität im Übersetzungsprozess zu sichern.

Das Berufsbild von Übersetzer:innen war und ist auch infolge der technologischen Entwicklung einem ständigen Wandel unterworfen. In der Fachliteratur wird diesbezüglich von einer Segmentierung oder Fragmentierung der Übersetzungsarbeit gesprochen (vgl. beispiels-

<sup>3</sup> Siehe dazu beispielsweise <https://bdue.de/fuer-presse-medien/presseinformationen/pm-detail/chatgpt-co-bedroht-kuenstliche-intelligenz-die-berufe-der-uebersetzer-und-dolmetscher> (09.09.2024).

weise Risku/Rogl/Milošević 2020). Die Vielfalt und das Volumen der Übersetzungsaufträge, die fachliche Komplexität der Inhalte von Ausgangstexten, der damit zusammenhängende Zeitfaktor, die technische Bearbeitung der Aufträge sowie die aktuellen Anforderungen des Arbeitsmarktes haben demzufolge auch das Kompetenzprofil von Übersetzer:innen wesentlich verändert. So werden Übersetzer:innen immer mehr zu multiprofessionellen Expert:innen, die einen Text nicht nur übersetzen können, sondern auch über Fertigkeiten verfügen, die über den eigentlichen, im engen Sinne verstandenen translatorischen Prozess hinausgehen. Hierzu zählen Fertigkeiten wie Pre-Editing, Post-Editing, Untertitelung, Lokalisierung, Erstellung und Verwaltung von Terminologiedatenbanken, Projektmanagement u. v. a. (vgl. Sandrini 2022).

Auch im EMT-Kompetenzrahmen (2022) wird die Vielschichtigkeit des Übersetzungsberufs bekräftigt, d. h. die vielen unterschiedlichen Kompetenzen und Fertigkeiten, die notwendig sind, um Bedeutung von mindestens einer natürlichen Sprache in eine andere zu übertragen, und die Vielzahl unterschiedlicher Aufgaben, die mit der Erbringung von Übersetzungsleistungen verknüpft sind. Die im EMT-Kompetenzrahmen enthaltene Technologie-Kompetenz (neben den sonstigen Kompetenzen bzgl. Sprache und Kultur, Übersetzungs-, persönliche und interpersonelle sowie Dienstleistungskompetenz) umfasst dabei alle Kenntnisse und Fertigkeiten, die bei der Anwendung gegenwärtiger und künftiger Übersetzungstechnologien im Übersetzungsprozess zum Einsatz kommen. Miteingeschlossen werden dabei auch Grundkenntnisse der MT-Technologien und die Fähigkeit, die maschinelle Übersetzung bedarfsorientiert einzusetzen (EMT-Kompetenzrahmen 2022: 9).

## 2 Maschinelle Übersetzung im Dienst der juristischen Übersetzung

Eine Sonderstellung nimmt die maschinelle Übersetzung im Bereich der Rechtsübersetzung ein. Um dies zu verdeutlichen, soll im Folgenden kurz der Fokus auf die signifikanten Eigenschaften der Rechtsübersetzung gerichtet werden.

Die Rechtsübersetzung gilt als eine der schwierigsten Arten der Übersetzung. Der Schwierigkeitsgrad ergibt sich zunächst einmal aus der Gegebenheit, dass die juristische Übersetzung als eine „spezifische Form des Kulturtransfers“ (Reiß/Vermeer 1984: 13) betrachtet wird. Diese Spezifik ist dadurch begründet, dass bei der Übersetzung nicht nur ein sprachlicher Informationstransfer stattfindet, sondern auch ein Transfer von mentalen Konzepten zwischen zwei voneinander abweichenden Rechtssystemen (so bei Rechtsübersetzungen, die nicht innerhalb einer mehrsprachigen nationalen Rechtsordnung erfolgen).

Die einzelnen nationalen Rechtssysteme sind als Ergebnis einer historischen Entwicklung zu betrachten und sind fest in ein bestimmtes kulturelles Umfeld eingebettet. Diese historisch-kulturelle Einbettung bestimmt folglich die in dem jeweiligen Rechtssystem geltenden Rechtsnormen und ihre Interpretation, die das Verhalten von Mitgliedern einer Gesellschaft durch Verbote, Gebote oder Erlaubnisse regeln. Mit anderen Worten: Bei der Übersetzung von Rechtstexten wird nicht nur von der Ausgangssprache in die Zielsprache übersetzt, sondern von einem Rechtssystem in ein anderes (siehe Modellsituation 3 von Sandrini 1996).<sup>4</sup>

<sup>4</sup> Jeder Rechtstext ist immer in einen bestimmten Kommunikationsrahmen eingebettet. Bei der Übersetzung von Rechtstexten sind daher vor allem zwei Faktoren zu berücksichtigen: der Grad der Nähe zwischen der Ausgangs- und Zielsprache und der Grad der Nähe zwischen Ausgangs- und Zielrechtssystem. Hinsichtlich des Zusammenhangs zwischen Sprache und Rechtssystem und ihrer (relativen) Nähe unterscheidet Sandrini (1996) in der translingualen Praxis drei grundlegende Modellsituationen: 1. meh-

Die kulturelle Verankerung des Rechts spiegelt sich einerseits in der teilweise unterschiedlichen Auslegung von Rechtsbegriffen und der daraus folgenden Festlegung der Terminologie, andererseits aber auch im spezifischen Stil des juristischen Diskurses wider, der für die jeweiligen Sprachen und einzelne Textsorten charakteristisch ist. In diesem Zusammenhang wird von einer bestimmten Tradition der sprachlichen „Exteriorisierung“ juristischer Inhalte gesprochen (Hoffmann 1983: 614). Dies betrifft insbesondere die schriftliche Fixierung von Rechtsnormen und -vorschriften sowie die Konventionen juristischer Textsorten.

Genauigkeit und Exaktheit bei der Übersetzung von Rechtstexten und die damit verbundene Verständlichkeit der Äußerung sind weitere Attribute, die die juristische Übersetzung kennzeichnen. Bei der Übersetzung muss die sogenannte Rechtssicherheit der Übersetzung gewährleistet sein, um eventuelle Missverständnisse in der Rechtskommunikation als Folge einer falschen Übersetzung zu vermeiden. Rezipient:innen einer juristischen Übersetzung können Fachleute mit juristischer Ausbildung sein, aber auch Laien mit wenig oder gar keinem juristischen Wissen (Wiesmann 2004: 17). Viele juristische Textsorten (Urteil, Anklageschrift, Gesetz u. a.) haben jedoch nicht nur einen streng definierten und abgegrenzten Adressatenkreis, sondern richten sich oft an mehrere Empfängergruppen gleichzeitig. Auch diese Tatsache muss letztlich bei der Auswahl geeigneter Übersetzungsstrategien und -lösungen in der juristischen Übersetzung berücksichtigt werden (siehe dazu Wrede 2020). Übersetzer:innen werden also mit dem Rechtssystem, der Rechtssprache und der Terminologie der Ausgangs- und der Zielkultur konfrontiert, und ihre Aufgabe besteht darin, die Informationen so zu transformieren, dass sie im Zielrechtssystem im Sinne der Skopos-Theorie ihren funktionalen Zweck erfüllen (Reiß/Vermeer 1984: 101).

Eine weitere Besonderheit juristischer Übersetzungen, die sich aus der Verankerung der Rechtssysteme in einem bestimmten kulturellen Umfeld ergibt, ist eine nur teilweise Äquivalenz bzw. Nulläquivalenz von Rechtsbegriffen (vgl. Stolze 1992, Koller 2001, Arntz/Picht/Mayer 2009,). Stolze (1992: 223) argumentiert, dass es selbst innerhalb der Fachsprache (Stil) erhebliche Unterschiede gibt, die sich auf terminologische Präzision, Eindeutigkeit und Systematik beziehen. Als Beispiel nennt sie die Natur- und Ingenieurwissenschaften mit mehr oder weniger genau definierten Begriffen innerhalb eines Begriffssystems, während die Sozial- und Geisteswissenschaften, einschließlich der Rechtswissenschaften, in Bezug auf ihre Auslegung offener sind. Eine ähnliche Auffassung vertreten Abrahámová/Škvareninová (2006: 98), denen zufolge das eigentliche Problem der juristischen Übersetzung die Vielfalt der Rechtssysteme ist.

Die Tatsache, dass es keine identischen Rechtssysteme und keine identischen definitiven Bestimmungen von Rechtsbegriffen gibt, führt dazu, dass die Übersetzung von Rechtsbegriffen aus methodischer Sicht einen spezifischen komparativen Ansatz erfordert (Rechtsvergleichung). Eine Besonderheit der Übersetzung von Rechtstexten ist daher der Vergleich von Rechtssystemen bzw. der Vergleich der Rechtsterminologien, die den jeweiligen Rechtssystemen eigen sind und sich historisch herausgebildet haben (vgl. Pommer 2006, Tomášiková 2017 u. a.).

Spezifisch für die juristische Übersetzung ist außerdem die Komplexität und inhaltliche Sättigung von Rechtstexten. In Anbetracht der Tatsache, dass das Recht die Beziehungen zwischen den Bürger:innen untereinander und zwischen den Bürger:innen und dem Staat (inner-

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rere Sprachen vs. ein Rechtssystem, 2. eine Sprache vs. verschiedene Rechtssysteme und 3. verschiedene Sprachen vs. verschiedene Rechtssysteme (vgl. auch Ďurčo 2004, Wrede 2020 u. a.).

staatliches Recht) bzw. zwischen den einzelnen Staaten (internationales Recht) regelt und somit praktisch alle Bereiche des menschlichen Daseins umfasst, ist es für fast jeden Rechtstext charakteristisch, dass er nicht ausschließlich mit dem Fachvokabular (Terminologie) des Rechts arbeitet, sondern auch mit der Terminologie anderer Fachbereiche. Dies ist wiederum davon abhängig, welche Sachverhalte im Text abgehandelt werden (Sandrini 2010: 143). Griebel (2013: 133) und auch Stolze (2014: 272) weisen in diesem Zusammenhang auf ein weiteres Phänomen der Rechtssprache hin, indem sie eine besondere Nähe der Rechtssprache zur Allgemeinsprache hervorheben. Dies hat zur Folge, dass ein Rechtstext durchaus polysemische Ausdrücke enthalten kann. Ein Ausdruck aus dem allgemeinen Wortschatz wird im rechtlichen Kontext, ähnlich wie Termini in anderen Fachgebieten, jedoch begrifflich neu definiert.<sup>5</sup>

Die Übersetzung juristischer Texte zeichnet sich schließlich auch dadurch aus, dass die Komplexität des Fachdiskurses – mehr als bei anderen Arten der Fachübersetzung – einen streng interdisziplinären Ansatz erfordert. Gleichzeitig basiert das Postulat der Interdisziplinarität bei der Übersetzung juristischer Texte in erster Linie auf der Verknüpfung des Wissens der einzelnen juristischen Disziplinen, der allgemeinen und vergleichenden Sprachwissenschaft, der Textlinguistik, der Terminologielehre und der Translationswissenschaft (Rakšányiová 2014: 34).

Aufgrund der sprachlichen Beschaffenheit der Rechtstexte, der nicht selten voneinander abweichenden definitiven Bestimmungen der Rechtsbegriffe in den jeweiligen Rechtssystemen, der kaum vorhandenen Volläquivalenz der Rechtstermini sowie auch aufgrund der Komplexität und Vielschichtigkeit des juristischen Diskurses erweist sich der Einsatz maschineller Übersetzungssysteme in der juristischen Übersetzung unter Berücksichtigung der Übersetzungsqualität und vor allem der erforderlichen Rechtssicherheit des Outputs demnach als zumindest nicht gerade leichtes Unterfangen.

Schlüter-Ellner (2019: 277) benennt einige Faktoren, die für den Einsatz von Übersetzungssystemen (DeepL) in der Rechtsübersetzung hinderlich sein könnten. Es sind beispielsweise die terminologische Inkonsistenz über die Satzebene hinaus, die dem Prinzip der Eindeutigkeit widerspricht, die fehlende Beherrschung von komplizierten Satzstrukturen, die für den juristischen Diskurs typisch sind, wie auch die über *linguae* eingeflossenen EU-Texte, die auf der EU-Rechtsordnung beruhen und insofern nicht ohne Differenzierung für Übersetzungen von Texten aus den EU-Mitgliedsstaaten verwertbar sind, da diese auf der Grundlage nationaler Rechtsordnungen formuliert sind. Und da bei der Auslegung eines Rechtstextes oft ein einziges Wort oder eine bestimmte Formulierung für weitere Entscheidungen von Bedeutung sein und den Sinn der Behauptung maßgeblich beeinflussen kann, ist bei den Rechtsübersetzungen ein tiefgreifendes Post-Editing, d. h. der Eingriff eines/einer Humanübersetzer:in, mehr als notwendig.

Trotz der weiterhin bestehenden Unsicherheit und potenziellen Gefahren beim Einsatz der maschinellen Übersetzung im juristischen Bereich, kann auch angesichts der jüngsten Migrationsbewegungen erwartet werden, dass das Volumen an juristischen Übersetzungsaufträgen nicht nur innerhalb der EU-Institutionen, sondern auch auf der nationalen Ebene der jeweiligen Länder wachsen wird. Somit sind partielle Untersuchungen der Qualität und Fehlerhaftigkeit der maschinellen Übersetzung, ihrer Grenzen und Perspektiven in den jeweiligen

<sup>5</sup> Beispielsweise steht der Ausdruck *Ruhen* in der Rechtssprache etwa für die Strafverfolgungsverjährung (vgl. § 78 b StGB), während er in der Gemeinsprache ‚Erholung durch Nichtstun‘ bedeutet (vgl. Duden 2019).

Sprachkombinationen durchaus von Belang. Inzwischen gibt es auch in dieser Hinsicht sprachpaarbezogene Studien, die sich mit der maschinellen Übersetzung und dem anschließenden Post-Editing oder dem Einsatz von MT-Systemen kritisch auseinandersetzen (vgl. Proia 2012, Gruntar Jermol 2019 und 2020, Mileto 2019, Munková/Wrede/Absolon 2019, Mustu 2019, Wrede/Munková/Welnitzová 2020, Rupcic 2021, Vigier-Moreno/Pérez-Macías 2022 u. a.). Von den jüngsten Studien sind hier als repräsentativ die folgenden kurz zu erwähnen.

Vigier-Moreno/Pérez-Macías (2022) untersuchen in ihrer Studie die Qualität englischer Übersetzungen eines spanischen Untersuchungsbefehls, die von drei verschiedenen neuronalen maschinellen Übersetzungssystemen (DeepL, eTranslation und Google Translate) unter Verwendung der TAUS-Bewertungsrichtlinien erstellt wurden. Die durchgeführte TAUS-Analyse bezog sich auf vier Kategorien: Genauigkeit, Sprachfluss, Terminologie und Stil. Wie die Ergebnisse zeigen, gab es unabhängig von dem verwendeten Übersetzungssystem die meisten Unstimmigkeiten in den Bereichen der Terminologie und der Genauigkeit (Vigier-Moreno/Pérez-Macías 2022: 85).

Die maschinelle Übersetzung (DeepL) typischer Wortkombinationen (Kollokationen) und der Terminologie in normativen Texten aus dem Deutschen ins Englische wurde von Gruntar Jermol (2019) am Beispiel des deutschen Strafgesetzbuches analysiert. Gruntar Jermol (2019: 144) kommt zur Erkenntnis, dass neuronale maschinelle Übersetzungssysteme überaus fortschrittlich sind. Im Bereich der Rechtssprache, wo Genauigkeit und Konsequenz stets im Dienste der Rechtssicherheit stehen (insbesondere auf lexikalischer Ebene bei Terminologie und terminologischen Kollokationen), sind diese jedoch weiterhin noch nicht ausreichend ausgereift.

Mustu (2019) nimmt in seiner Untersuchung mittels DeepL erstellte Übersetzungen von Verträgen aus dem Englischen ins Deutsche unter die Lupe. Er fokussiert dabei auf Fehler bei Fachbegriffen, Adverbien, Präpositionen, Wortpaaren, Mehrwortbenennungen, aber auch auf sog. *false friends* und *true friends*. Als Fazit seiner Untersuchung hält Mustu fest (2019: 276):

DeepL ist eine kleine Revolution, ersetzt den Übersetzer aus Fleisch und Blut aber nicht. Probleme mit Fachbegriffen, Sprachpaaren und manchen Adverbien, eine starke Verhaftung in der Struktur und dem Satzbau des Originals, und Inkohärenz bei wiederholt auftretenden Begriffen, treten zu Tage. Somit ist gute Nachricht: DeepL hilft. Die schlechte: ein Profi muss nachhelfen. Aber das ist eigentlich eine gute für Übersetzer, denn sie müssen ihr Berufsbild wegen DeepL zurzeit nicht redefinieren.

Wiesmann (2019) setzt sich in ihrer Untersuchung wiederum mit der Frage auseinander, inwieweit die maschinelle Übersetzung in der Lage ist, italienische juristische Texte oder zumindest bestimmte juristische Textsorten so gut ins Deutsche zu übersetzen, dass sich der Nachbearbeitungsaufwand (Post-Editing) in Grenzen hält. Um diese Frage zu beantworten, wurden DeepL, ein maschinelles Übersetzungssystem, und MateCat, ein CAT-System, das maschinelle Übersetzung integriert, getestet. Die Auswertung erfolgte nach den Kriterien Verständlichkeit und Aussagekraft des Zieltextes und Übereinstimmung zwischen Ausgangs- und Zieltext unter Berücksichtigung der konkreten Übersetzungssituation. Da die Bewertung der Übereinstimmung zwischen Ausgangs- und Zieltext grundsätzlich schlechter ausfiel als die der Sinnhaftigkeit des Zieltextes, sollte nach Wiesmann die Ausbildung von angehenden Übersetzer:innen verstärkt darauf abzielen, das Bewusstsein für die Unterschiede zwischen maschineller und menschlicher Übersetzung zu schärfen und das juristische Fachwissen

zu stärken. Zu ähnlichen Schlussfolgerungen gelangten auch Vigier-Moreno/Pérez-Macías (2020).

Der Gegenstand der Untersuchung von Munková/Wrede/Absolon (2019) ist die maschinelle Übersetzung der Belehrung eines Beschuldigten aus dem Slowakischen ins Deutsche mittels Google Translate. In der Studie wurde die Qualität menschlicher, maschineller und post-edierter maschineller Übersetzung bewertet und miteinander verglichen. Die Ergebnisse zeigen, dass das Post-Editing maschineller Übersetzung in Bezug auf die Produktivität und das Fach- und Terminologiewissen der menschlichen Übersetzer:innen effektiver ist als menschliche Übersetzung. In Bezug auf die Qualität (Satzstruktur oder Stilistik) ist die menschliche Übersetzung unabhängig von der Zeit von höherer Qualität als maschinelle Übersetzung, aber ähnlich gut wie das Post-Editing. Die Post-Editor:innen wurden von der Grammatik und der Stilistik der maschinellen Übersetzung beeinflusst, bearbeiteten in der selben Zeit aber ein größeres Volumen an maschineller Übersetzung als menschliche Übersetzer:innen (Munková/Wrede/Absolon 2019: 18). Zu vergleichbaren Schlussfolgerungen gelangte in ihrer Studie auch Mileto (2019).

Eine der bislang komplexesten Fallstudien zum Einsatz maschineller Übersetzungssysteme in der juristischen Übersetzung liefert Rupcic (2021) in ihrer Monografie *Einsatzpotenziale maschineller Übersetzung in der juristischen Fachübersetzung*. Rupcic untersucht anhand der Übersetzung eines englischen Vertragstextes ins Deutsche, inwieweit neuronale Übersetzungssysteme (DeepL) nicht nur grammatische, lexikalische und stilistische Faktoren, sondern auch pragmatische und kontextuale Gegebenheiten eines Rechtstextes berücksichtigen können. Ein besonderer Schwerpunkt der Untersuchung liegt dabei auf dem Umgang neuronaler Übersetzungssysteme mit Kohäsion und Kohärenz. Rupcic (2021: 206) kommt anhand ihrer Untersuchung zum Schluss, dass die neuronalen maschinellen Übersetzungssysteme im Hinblick auf Aspekte wie Kohäsion und Kohärenz einerseits durchaus geeignete Hilfsmittel für die Rechtsübersetzung sind, andererseits aber beim Einsatz maschineller Übersetzung nach wie vor bestimmte Problembereiche identifiziert werden. Zu den wesentlichen Problemen zählen: 1. inhaltliche Fehler, die manchmal offensichtlich sind, manchmal aber nur schwer identifiziert werden konnten; 2. Defizite hinsichtlich der fach- bzw. zielsprachlichen und registerbezogenen Konventionen infolge der mangelhaften Berücksichtigung pragmatischer Aspekte des Übersetzungsauftrags und 3. nicht konsistente bzw. nicht nachvollziehbare Vorgehensweise.

### 3 Zum Entwurf des ersten ungarischen Zivilgesetzbuches

Gegenstand der nachfolgenden Analyse maschineller Übersetzung und ihres Vergleichs mit menschlicher Übersetzung ist das *Erbrecht* im Entwurf des ersten ungarischen Zivilgesetzbuches (1901). Das *Erbrecht* wurde bereits vorher ins Slowakische übersetzt (2020–2021), weshalb es zum Zweck der Vergleichsanalyse (menschliche versus maschinelle Übersetzung) geeignet zu sein scheint. Es handelt sich um einen aus dem Jahr 1900 stammenden Text, der kurz nach seiner Entstehung aus dem Ungarischen ins Deutsche übersetzt wurde. Die deutsche Version des EBG (sein erbrechtlicher Teil) kann daher aufgrund seines Entstehungskontextes für eine Originalquelle gehalten werden. Deutsch als damalige Lingua franca des mitteleuropäischen Raumes war u. a. auch als Sprache der Juristen (Existenz der Donaumonarchie) sehr wichtig. Durch die Übersetzung des EBG ins Deutsche wollte man vermutlich die österreichische Rechtswissenschaft bekannt machen.

Da der Text vor mehr als 100 Jahren entstanden ist, soll zuerst kurz auf seinen rechtshistorischen Hintergrund eingegangen werden. Hamza (2006: 5) erläutert diesen wie folgt:

Das Bestreben, ein Zivilgesetzbuch zu verabschieden, beherrschte von dem Jahre 1895 an die ungarische Rechtspolitik. Einen der konsequentesten Anhänger dieser Bestrebung findet man in dem ungarischen Romanisten und Zivilisten Gusztáv Szászy-Schwarz. Sein aus 2043 Paragraphen bestehender Entwurf wurde im Jahre 1900 vollendet, als der namhafte Prozessrechtler Sándor Plósz (1846–1925) Justizminister war. Im Gegensatz zu den früheren Teilentwürfen ist dieser Entwurf (genannt auch der erste Entwurf) umfassend. Im Aufbau und in den Rechtsinstituten ist der Einfluss des deutschen BGB eindeutig festzustellen. Der Entwurf gliedert sich in vier Teile: Personen- und Familienrecht, Schuldrecht, Sachenrecht und Erbrecht. Die Funktionen des fehlenden Allgemeinen Teils werden in diesem Kodifikationswerk von den ersten Titeln des Schuldrechts wahrgenommen, die immerhin einem „versteckten“ Allgemeinen Teil gleichkommen. Hinsichtlich der Rechtsgeschäfte folgt dieser Entwurf der Erklärungstheorie.

Der Entwurf (als materielles Erbrecht) hat *Gesetz*, *Testament* und *Erbvertrag* als Berufungsgründe beibehalten und baut auf den Prinzipien des ursprünglichen ungarischen Erbrechts auf. Vor allem hielt der Entwurf des ersten ungarischen Zivilgesetzbuches aus dem Jahr 1900 (EBG) ziemlich streng an dem an den Tod des Erblassers gebundenen Delationsprinzip fest und zeichnete sich u. a. dadurch aus, dass die Universalsukzession beim Rechtsgeschäft *mortis causa* nicht obligatorisch war. Hiermit hängt die Tatsache zusammen, dass die testamentarische Verfügung auch ohne Erbeinsetzung möglich war. Es kann festgehalten werden, dass der EBG eine deutlich modernisierende, zum großen Teil gleichberechtigende Normierung der Erbfolge von Nachkommen erzielte, und zwar dadurch, dass zwischen dem Vermögen aus Erbschaften und dem erworbenen Vermögen kein Unterschied gemacht wurde.

Der EBG hat die Intestaterbfolge auf fünf gesetzliche Erbgruppen beschränkt, womit eine sehr anstrengende Ermittlung der Erben *in infinitum* aufgehoben wurde. Ebenfalls hat man die Rechtsinstitute der *Witwenerbfolge* und des *Witwenrechts* verworfen und die Rechte der Witwe neu geregelt. Die Überreste des historischen ungarischen Rechts sind in der Regelung der Testaterbfolge durch die Beibehaltung der einzelnen Testamentstypen (öffentliches, privates und privilegiertes Testament) und des Erbvertrags zu finden (Gergel/Švecová 2021: 145–147).

## 4 Untersuchung

### 4.1 Methodologie

Gegenstand der Untersuchung ist der Vergleich der Qualität maschineller und menschlicher Übersetzung eines Rechtstextes aus dem Deutschen ins Slowakische. Untersucht wurde die Qualität der maschinellen Übersetzung an einem Auszug aus dem Entwurf des ersten ungarischen Zivilgesetzbuches (Teil Erbrecht) im Umfang von 763 Segmenten. Beim Ausgangstext handelt es sich um einen Text, der kurz nach seiner Entstehung (1900) aus dem Ungarischen ins Deutsche übersetzt wurde (siehe Kapitel 3).

Für die maschinelle Übersetzung wurden drei frei zugängliche, auf neuronalen Netzen basierte Übersetzungsdienste – DeepL (DL), Google Translate (GT) und eTranslation (ET) – sowie das Sprachmodul ChatGPT (GPT) verwendet. Die maschinell erzeugten Übersetzungen des erbrechtlichen Textes aus dem Deutschen ins Slowakische wurden mit der menschl-

chen Übersetzung, die von einem professionellen Übersetzer in Zusammenarbeit mit einer Juristin angefertigt wurde, verglichen (Gergel/Švecová 2021). Bei der menschlichen Übersetzung des gegenständlichen Rechtstextes aus dem Deutschen ins Slowakische wurde sowohl auf die Rechtsinhalte und -zusammenhänge als auch auf die einschlägige Terminologie und auf die stilistischen und pragmatischen Besonderheiten des Rechtsdiskurses beider involvierter Rechtssysteme und Sprachen eingegangen, womit ein interdisziplinärer Zugang zwischen Translationswissenschaft und Rechtswissenschaft gewährleistet wurde.

Da die Terminologie als Grundlage jedes Fachdiskurses angesehen wird und durch Termini der Sachverhalt zu einem wesentlichen Teil dargeboten und die jeweilige Fachsprache reglementiert wird, wird im vorliegenden Beitrag vorrangig auf die Korrektheit der Übersetzung des terminologischen Bestands des Erbrechts aus dem Deutschen ins Slowakische eingegangen. Dies ist auch dadurch bedingt und für die Untersuchung interessant, dass Slowakisch und Deutsch genealogisch verwandte Sprachen sind (beide Sprachen gehören der indoeuropäischen Sprachfamilie an) und somit einige Ähnlichkeiten aufweisen (flektierende Merkmale, ähnliches Kasussystem, relativ freie Wortstellung, Agglutinationsmerkmale u. a.). Dennoch gibt es zwischen Deutsch (einer germanischen Sprache) und Slowakisch (einer slawischen Sprache) sprachsystembedingte Unterschiede, die die Qualität der maschinellen Übersetzung beeinflussen können. Deutsch zeichnet sich beispielsweise im Unterschied zu Slowakisch durch Bildung von Komposita aus, wohingegen das Slowakische in analogen Fällen als flektierende Sprache meistens Verbindungen mit Attributen bildet (*Erbvertrag – dedičská zmluva, Zweitlegatar – druhý odkazovník*). Deutsch hat auch mehr isolierte Merkmale, da der Kasus durch den Artikel, im Slowakischen jedoch durch Endungen ausgedrückt wird (*dem öffentlichen Notar – verejnému notárovi*). Auch die im Deutschen ausgeprägte Tendenz zur syntaktischen Kondensation, analytische Vergangenheitsformen oder das Nichtvorhandensein der doppelten Negation im Unterschied zum Slowakischen können für eine Beeinträchtigung der Qualität des maschinell erzeugten Translats sorgen (siehe dazu ausführlich Bánik et al. 2019: 41–43).

#### 4.2 Textkorpus

Für die Zwecke der Untersuchung wurde ein Textkorpus zusammengestellt, das aus dem Ausgangstext und den vier dazu gehörigen maschinell erzeugten Übersetzungen besteht (Auszug aus dem Entwurf des ersten ungarischen Zivilgesetzbuches – Teil Erbrecht).

Der untersuchte Ausgangstext besteht aus 10 321 Token (eine Texteinheit, die aus Wörtern, Abkürzungen, Satzzeichen oder Zahlen besteht), die in kurze, Standard- und lange Sätze und Paragraphennummern unterteilt sind. In Anlehnung an Cutts (2013), der argumentiert, dass ein angemessener Satz zwecks besserer Lesbarkeit bzw. Verständlichkeit eines Textes 15 bis 20 Wörter enthalten sollte, sowie an Garner (2001), der darauf hinweist, dass beim Verfassen von Rechtstexten als Regel bis zu 20 Wörtern pro durchschnittlichem Satz befolgt werden sollte, wurde das hier untersuchte Korpus in kurze Sätze bis zu 10 Wörtern, Sätze mit Standardlänge zwischen 10 und 20 Wörtern, lange Sätze über 20 Wörter und Sätze, die nur Paragraphennummern enthalten, unterteilt (Tabelle 1).

Anschließend wurden von den insgesamt 130 erbrechtlichen Termini nur diejenigen ausgewählt, die im Ausgangstext öfter als 10 Mal vorkommen. Nach diesem Kriterium wurden dann 19 erbrechtliche Begriffe näher untersucht, wobei in dem vorliegenden Beitrag nur die 4 am häufigsten vorkommenden Termini exemplarisch analysiert und besprochen werden.

Eine kurze Charakteristik des Textkorpus (Lesbarkeit, lexikalisch-grammatikalische Merkmale) ist in Tabelle 1 angeführt.

Tab. 1: Charakteristik des Textkorpus

Merkmale	Merkmalsbezeichnung	Menschliche Übersetzung (HT)	Ausgangstext (VT)	ChatGPT (GPT)	DeepL (DL)	Google Translate (GT)	eTranslation (ET)
Lesbarkeit	Sätze, die nur Paragraphennummern enthalten (z. B. § 1799)	251	251	251	251	251	251
	Sätze ohne Paragraphennummern	512	512	512	512	512	512
	Durchschnittliche Satzlänge (in Wörtern)	15,79	20,20	17,40	17,78	17,60	17,04
	Durchschnittliche Wortlänge (in Zeichen)	6,18	6,17	5,80	5,67	5,56	5,72
	Anzahl der kurzen Sätze ( $n < 10$ )	138	90	115	115	118	122
	Anzahl der Standardsätze ( $10 \leq n < 20$ )	214	174	208	193	196	216
	Anzahl der langen Sätze ( $n \geq 10$ )	160	248	189	204	198	174
Lexikalisch-grammatikalische Merkmale	Frequenz der Substantive	2851	2706	2841	3067	3065	3046
	Frequenz der Adjektive	1085	825	1276	1069	1039	1029
	Frequenz der Verben	1086	920	1069	1117	1130	1047
	Frequenz der Artikel	550	2.156	550	613	581	599
	Frequenz der Präpositionen	1037	1187	1071	1119	1055	1060
	Frequenz der Eigennamen	316	396	348	292	89	77
	Häufigkeit der koordinierenden Konjunktionen	350	350	373	386	355	345
	Häufigkeit der subordinierenden Konjunktionen	361	170	372	400	399	395
	Frequenz der Adverbien	204	449	166	187	231	170
	Frequenz der Pronomen	404	653	354	401	400	390

Merkmale	Merkmalsbezeichnung	Menschliche Übersetzung (HT)	Ausgangstext (VT)	ChatGPT (GPT)	DeepL (DL)	Google Translate (GT)	eTranslation (ET)
	Frequenz der Hilfsverben	210	606	292	226	243	282
	Frequenz der Numeralien	494	383	462	491	476	470
	Häufigkeit der Partikel	230	220	222	228	234	222
	Frequenz der Satzzeichen	1319	1495	1471	1522	1553	1536
	Sonstiges	25	0	8	7	6	6

Aus den korpusbasierten Statistiken (Tabelle 1) ergibt sich, dass sich die maschinellen Übersetzungen nicht nur in der Anzahl der langen und kurzen Sätze, sondern auch in der Häufigkeit des Auftretens einzelner Wortarten voneinander unterscheiden. Bei der Anzahl der kurzen Sätze (mit bis zu 10 Wörtern) waren beispielsweise DeepL und Google Translate bei der Übersetzung insofern konsistent, als beide Systeme 145 kurze Sätze produzierten. Während Google translate um 3 kürzere Sätze mehr übersetzte, übersetzte eTranslation bis zu 7 Sätze mehr. Es stellt sich heraus, dass die beiden letztgenannten maschinellen Übersetzer dazu neigen, die Anzahl der Sätze zu erhöhen, im Gegensatz zu den ersten beiden, die konsistent sind, die sich also nicht in der Anzahl der übersetzten kurzen Sätze unterscheiden. Ein weiteres interessantes Ergebnis ist, dass die menschliche Übersetzung bis zu 138 kurze Sätze enthielt, was darauf hindeutet, dass die von eTranslation erstellte maschinelle Übersetzung der menschlichen Übersetzung am nächsten kommt (122). Interessante Statistiken lassen sich auch bei langen Sätzen beobachten. Die meisten langen Sätze wurden von DeepL produziert (204 Sätze), gefolgt von Google Translate (198 Sätze) – die wenigsten vom menschlichen Übersetzer:innen (nur 160 Sätze). Die durch das eTranslation-System erstellte Übersetzung enthielt 122 kurze Sätze, jene von ChatGPT und DeepL dagegen nur 115.

Ein weiteres interessantes Ergebnis ist die Disparität bezüglich des Vorkommens von Substantiven, Adjektiven und Verben im Ausgangstext und den jeweiligen maschinell erstellten Übersetzungen. Die 2706 im Ausgangstext vorkommenden Substantive wurden durch DeepL mit 3067 und durch Google Translate mit 3065 Substantiven übersetzt. ChatGPT verwendete dagegen nur 2841 Substantive. Im Vergleich zur menschlichen Übersetzung (2851 Substantive) kam die von ChatGPT erstellte maschinelle Übersetzung der menschlichen Übersetzung am nächsten. Ein ähnliches Ergebnis ist auch bei den Adjektiven zu verzeichnen. 825 Adjektive im deutschsprachigen Ausgangstext wurden von den eingesetzten Übersetzungssystemen ins Slowakische quantitativ unterschiedlich übersetzt (DeepL 1069 Adjektive, Google Translate 1039 Adjektive, ChatGPT 1276 Adjektive, eTranslation 1029 Adjektive). Der menschlichen Übersetzung (1085 Adjektive) kam die maschinelle Übersetzung durch DeepL am nächsten.

Bei den Verben waren die hier verwendeten maschinellen Übersetzungssysteme kohärenter. Waren im Ausgangstext 920 Verben verzeichnet, bewegte sich die Anzahl der Verben in den slowakischen Übersetzungen in einem Rahmen von 1047 bis 1117 Verben, wobei ChatGPT der menschlichen Übersetzung (1086) am nächsten kam.

Bei der Übersetzung von deutschen Adverbien (449 im Ausgangstext) ins Slowakische schwankten die maschinellen Übersetzungssysteme deutlich (ChatGPT 166 Adverbien,

eTranslation 170 Adverbien, DeepL 187 Adverbien). Die maschinelle Übersetzung von Google Translate (231 Adverbien) kam dabei der menschlichen Übersetzung am nächsten (204).

Im Folgenden wird aus Platzgründen lediglich die deutsche erbrechtliche Terminologie und ihre maschinell erzeugte Wiedergabe ins Slowakische einer Analyse unterzogen, um die Genauigkeit und Angemessenheit der maschinellen Übersetzung zu beurteilen. Hierbei wird untersucht, wie spezifische Begriffe des deutschen Erbrechts in maschinellen Übersetzungen ins Slowakische übertragen werden und ob bzw. inwieweit dabei die terminologische Präzision gewährleistet ist.

#### 4.3 Forschungsannahmen

Auf Grundlage der Korpusstatistik (Tabelle 1) wurde angenommen, dass es einen statistisch signifikanten Qualitätsunterschied ( $p < 0,001$ ) zwischen den untersuchten maschinellen Übersetzungen gibt. Zugleich wurde die Frage aufgeworfen, ob eine der untersuchten maschinellen Übersetzungen die menschliche Parität erreicht.

Wie aus der Tabelle 1 ersichtlich, unterscheiden sich die maschinellen Übersetzungen nicht nur in Bezug auf Lesbarkeit und Komplexität voneinander, sondern auch in Bezug auf die Nähe (Genauigkeit) zur menschlichen Übersetzung. Daher werden die untersuchten maschinellen Übersetzungen mit der menschlichen Übersetzung mittels der standardisierten automatisierten BLEU-Metrik verglichen, die die Genauigkeit einer maschinellen Übersetzung im Vergleich zu einer Referenz (in diesem Fall zur menschlichen Übersetzung) misst. Es wird versucht zu bestimmen, welche der untersuchten maschinellen Übersetzungen der Qualität der menschlichen Übersetzung auf Grundlage von einem bis zu vier aufeinander folgenden Wörtern (1- bis 4-Gramm) am nächsten kommt. Im Fokus des Interesses steht die Frage, inwieweit die untersuchten maschinellen Übersetzungen die menschliche Parität erreichen, daher wird in der Analyse die Rangfolge der maschinellen Übersetzungen in Bezug auf die Nähe (Genauigkeit) zur menschlichen Übersetzung bestimmt. Diesbezüglich wurde die folgende statistische Hypothese aufgestellt:

*H0: Die maschinelle Übersetzung mittels DeepL/eTranslation/Google Translate/ChatGPT erreicht die Qualität der menschlichen Übersetzung, ausgedrückt durch die BLEU-Metrik ( $n = 1, 2, 3$  und  $4$ ).*

#### 4.4 Methoden

Zwecks Verifizierung der aufgestellten Hypothese wurde die Standardmetrik *BLEU-n* angewendet (Papineni et al. 2002), um die Qualität einer maschinellen Übersetzung zu bewerten, wenn die menschliche Übersetzung (referentielle Übersetzung) verfügbar ist. Die BLEU-n-Metrik basiert auf der lexikalischen Übereinstimmung zweier Strings (n-Gramme,  $n = 1, 2, 3$  oder  $4$ ). In dem vorliegenden Fall geht es um die maschinelle und die menschliche Übersetzung. Die BLEU-Metrik repräsentiert zwei Qualitätseigenschaften der Übersetzung, nämlich die *Adäquatheit* und den *Sprachfluss*:

$$BLEU(n) = exp \sum_{n=1}^N w_n \log p_n \times BP.$$

$w_n$  = Gewichtungsfaktoren für verschiedene Genauigkeiten  $p_n$

$$BP = \begin{cases} 1, & \text{if } r > r \\ e^{1-\frac{r}{h}}, & \text{if } h \leq r \end{cases}$$

$r$  = Referenz zur maschinellen Übersetzung  $h$

Bei den Qualitätseigenschaften der Übersetzung handelt es sich um das Kriterium der Adäquatheit des Transfers (der Angemessenheit der Übersetzung dem Ausgangstext gegenüber) und das Kriterium des Sprachflusses der Übersetzung in der Zielsprache. Mit anderen Worten werden dabei die Adäquatheit der Bedeutungsübertragung (message/Botschaft) aus der Ausgangssprache in die Zielsprache sowie der Sprachfluss der Übersetzung (message/Botschaft) in der Zielsprache bewertet.

#### 4.5 Ergebnisse

Aufgrund der Ergebnisse des t-Tests für eine Stichprobe (Tabellen 2 bis 5) wird die statistische Hypothese auf dem Signifikanzniveau 0,001 abgelehnt. Diese besagt, dass die maschinelle Übersetzung in Bezug auf die lexikalische Ähnlichkeit (ausgedrückt durch die BLEU-n-Metrik) die Parität der menschlichen Übersetzung erreicht. Mit einer Wahrscheinlichkeit von 99,9 % besteht ein statistisch signifikanter Unterschied zwischen der maschinellen und der menschlichen Übersetzung (Referenz), d. h., mit einer Wahrscheinlichkeit von 99,9 % ist keine der maschinellen Übersetzungen der menschlichen Übersetzung lexikalisch ähnlich. Die maschinelle Übersetzung, die der menschlichen Übersetzung (d. h. der Referenzübersetzung) in Bezug auf die lexikalische Adäquatheit am nächsten kommt, ist die Übersetzung mittels DeepL (Rank 1, Durchschnitt 0,529), gefolgt von ChatGPT (Rank 2, Durchschnitt 0,509) und Google Translate (Rank 3, Durchschnitt 0,429). Am weitesten entfernt von der Referenzübersetzung ist die mittels eTranslation angefertigte maschinelle Übersetzung (Rank 4, Durchschnitt 0,390) (Tabellen 2 bis 5).

Tab. 2: Durchschnitt der BLEU-1-Metrik gegenüber der Referenzübersetzung

Anmerkung:  $p < 0,001$

	Rank	Mean	Std.Dv.	N	Std.Err.	Reference	t-value	df	P
BLEU-1_deepl	1	0,529	0,1916	763	0,0069	1,000	-67,900	762	0,0000
BLEU-1_etranslation	4	0,390	0,1537	763	0,0056	1,000	-109,671	762	0,0000
BLEU-1_google	3	0,429	0,1805	763	0,0065	1,000	-87,304	762	0,0000
BLEU-1_gpt	2	0,509	0,1961	763	0,0071	1,000	-69,148	762	0,0000

Ähnliche Ergebnisse wurden für Zwei-Wort-Phrasen (2-Gramme) erzielt, bei denen die Nullhypothese auch abgelehnt wird, d. h., es besteht ein statistisch signifikanter Unterschied zwischen maschinellen und menschlichen Übersetzungen in Bezug auf die lexikalische Adäquatheit und den Sprachfluss (Tabelle 3). Sollten die maschinellen Übersetzungen in eine Reihenfolge gebracht werden (von der nächsten bis zu der weitesten in Bezug auf die Referenzübersetzung, d. h. dem Rank entsprechend, was auch mit dem Durchschnitt korrespondiert), wäre die Reihenfolge dieselbe wie bei BLEU-1.

Tab. 3: Durchschnitt der BLEU-2-Metrik gegenüber der Referenzübersetzung

	Rank	Mean	Std.Dv.	N	Std.Err.	Reference	t-value	df	p
BLEU-2_deepL	1	0,448	0,2162	763	0,0078	1,000	-70,484	762	0,0000
BLEU-2_eTranslation	4	0,311	0,1446	763	0,0052	1,000	-131,608	762	0,0000
BLEU-2_google	3	0,351	0,1671	763	0,0060	1,000	-107,260	762	0,0000
BLEU-2_gpt	2	0,430	0,2206	763	0,0080	1,000	-71,415	762	0,0000

Die gleichen Ergebnisse lassen sich für Drei-Wort-Verbindungen (Tabelle 4) sowie Vier-Wort-Verbindungen (Tabelle 5) feststellen.

Tab. 4: Durchschnitt der BLEU-3-Metrik gegenüber der Referenzübersetzung

	Rank	Mean	Std.Dv.	N	Std.Err.	Reference	t-value	df	p
BLEU-3_deepL	1	0,382	0,2132	763	0,0077	1,000	-80,050	762	0,0000
BLEU-3_eTranslation	4	0,282	0,1551	763	0,0056	1,000	-127,903	762	0,0000
BLEU-3_google	3	0,316	0,1607	763	0,0058	1,000	-117,500	762	0,0000
BLEU-3_gpt	2	0,367	0,2159	763	0,0078	1,000	-81,019	762	0,0000

In allen vier Fällen wird die genaueste maschinelle Übersetzung mittels DeepL erstellt und die am wenigsten adäquate und am wenigsten flüssige ist die von eTranslation erstellte. Dies ist eine interessante Feststellung, da eTranslation ein DGT-Werkzeug der Europäischen Kommission ist, das auf Verwaltungstexten trainiert wird. Allgemein kann jedoch festgehalten werden, dass keine der maschinellen Übersetzungen die menschliche Parität erreichte.

Tab. 5: Durchschnitt der BLEU-4-Metrik gegenüber der Referenzübersetzung

	Rank	Mean	Std.Dv.	N	Std.Err.	Reference	t-value	df	p
BLEU-4_deepL	1	0,339	0,2110	763	0,0076	1,000	-86,570	762	0,0000
BLEU-4_eTranslation	4	0,261	0,1638	763	0,0059	1,000	-124,709	762	0,0000
BLEU-4_google	3	0,288	0,1634	763	0,0059	1,000	-120,296	762	0,0000
BLEU-4_gpt	2	0,326	0,2149	763	0,0078	1,000	-86,639	762	0,0000

Was die Wahrung der Übersetzungskonsistenz anbelangt, so waren die maschinellen Übersetzungen DeepL und ChatGPT am wenigsten konsistent. Beide maschinellen Übersetzungen erreichten die höchste Variabilität (Standardabweichung) im Vergleich zur menschlichen Übersetzung in allen vier Varianten der BLEU-n-Metrik (Abbildung 1).

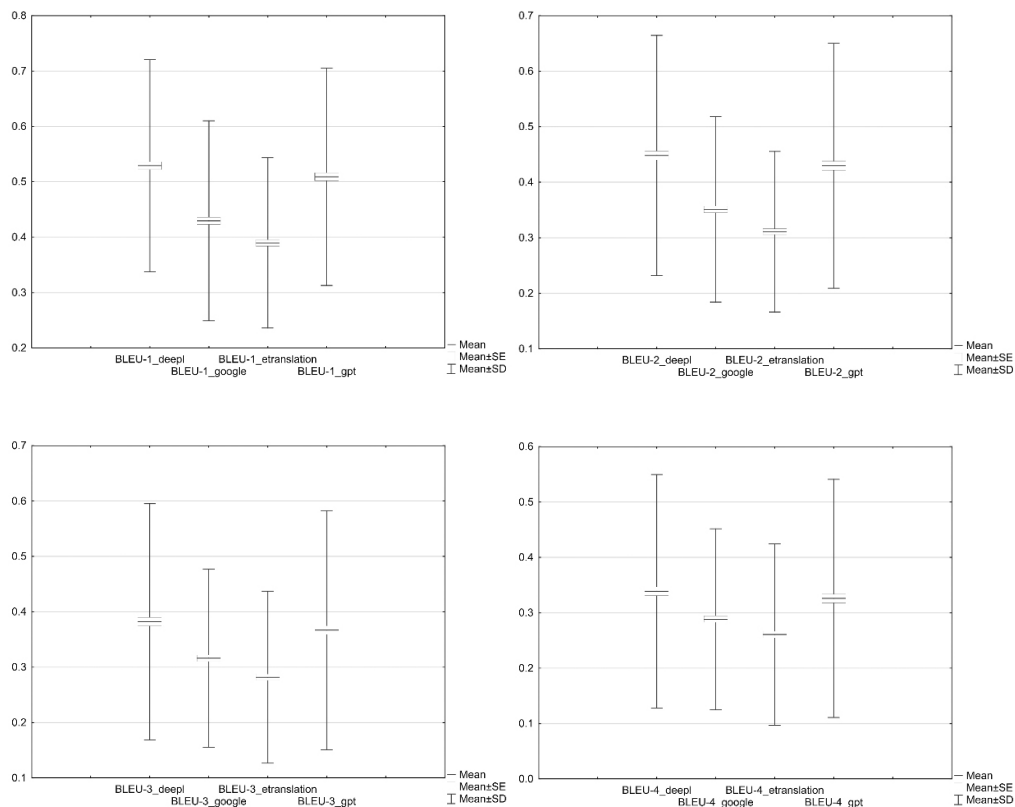


Abb. 1: Visualisierung deskriptiver Charakteristika: a) BLEU-1, b) BLEU-2, c) BLEU-3, d) BLEU-4

Obgleich die maschinellen Übersetzungen von DeepL und ChatGPT als Texte (vollständige Dokumente) in Bezug auf die lexikalische Adäquatheit und den Sprachfluss am genauesten waren, erreichten sie die geringste Konsistenz in Bezug auf die Terminologie. Andererseits ist bei den maschinellen Übersetzungen von Google Translate und eTranslation das umgekehrte Paradox zu beobachten. Obwohl die Gesamtqualität ihrer Übersetzungen niedriger ist als die von DeepL und ChatGPT, sind die maschinellen Übersetzungen von Google Translate und eTranslation konsistenter.

Diese Erkenntnis war der Anlass dazu, ausgewählte juristische Begriffe und die Vielfalt ihrer maschinellen Übersetzungen ins Slowakische zu untersuchen. Im Folgenden werden vier davon exemplarisch analysiert.

Der Terminus (*der*) *Erblasser* (*poručitel*) wurde in 156 von 763 Segmenten gefunden. Die Übersetzung ins Slowakische variierte bei den untersuchten maschinellen Übersetzungen (Tabelle 6).

Tab. 6: Vorkommen der maschinellen Übersetzung von (der) Erblasser

Terminus technicus	ChatGPT	DeepL	Google Translate	eTranslation
<i>Erblasser/Erblassera/Erblasserom</i>	49	0	0	0
<i>zosnulý</i>	45	12	12	48
<i>Zostaviteľ/zostaviteľa/zostaviteľ</i>	28	0	0	0
<i>Závetca/závetcom/závetcu</i>	13	22	3	103
<i>Testátor/testátora</i>	5	0	0	0
<i>Dedičom/dedičovi</i>	2	0	0	0
<i>dediča</i>	4	0	0	0
<i>zomrelý testátor/zomrelého testátora</i>	3	0	0	0
<i>Zomrelý/zomrelým</i>	2	0	0	0
<i>(doplnený preklad)</i>	2	0	2	0
<i>zanevretému/zanevretého</i>	2	0	0	0
<i>dedičstvo</i>	1	0	0	0
<i>poručiteľ</i>	0	119	134	5
<i>zanechávateľ</i>	0	2	0	0
<i>poručiteľov</i>	0	1	0	0
<i>poručiteľovo</i>	0	0	2	0
<i>zomretý</i>	0	0	2	0
<i>poručiteľový</i>	0	0	1	0

Wie man Tabelle 6 entnehmen kann, verwendete ChatGPT 12 verschiedene Übersetzungsvarianten für den Begriff *Erblasser*. 49 Mal wurde der Begriff in der Ausgangssprache belassen, 45 Mal wurde er als *zosnulý* ‚(Verstorbener)‘, 28 Mal als *zostaviteľ/zostaviteľ* (eigentlich *zústaviteľ* (tschech.) ‚Erblasser‘) und 13 Mal als *závetca* ‚(Letztwillig Verfügender)‘ übersetzt. Google Translate verwendete dagegen sieben Übersetzungsvarianten, DeepL fünf und eTranslation drei (*zosnulý*, *zostaviteľ* und *poručiteľ*). In Bezug auf die Übersetzungsgenauigkeit verwendeten jedoch nur DeepL und Google Translate weitgehend die korrekte Übersetzung *poručiteľ*.

Der Terminus *(der) Erbe (dedič)* kam in 131 von 763 Segmenten vor. Die maschinellen Übersetzungen des Wortes sind in der Tabelle 7 aufgeführt.

Tab. 7: Vorkommen der maschinellen Übersetzung von (der) Erbe

Terminus technicus	ChatGPT	DeepL	Google Translate	eTranslation
<i>dedič</i>	96	98	100	91
<i>dediča</i>	26	31	28	32
<i>osoba</i>	2	0	0	1

Terminus technicus	ChatGPT	DeepL	Google Translate	eTranslation
<i>dedičstvo</i>	1	0	0	2
<i>oprávnený</i>	1	0	0	0
<i>spoludedič</i>	1	0	0	0
<i>ona</i>	1	0	0	0
<i>poručiteľ</i>	0	0	1	0
<i>potomok</i>	0	0	0	2

Im Fall von ChatGPT wurden acht verschiedene Übersetzungsvarianten des Terminus (*der*) *Erbe* verwendet (96 Mal *dedič* – ‚der Erbe‘, 26 Mal *dediča* – ‚des Erben‘, 2 Mal *osoba* – ‚die Person‘ und jeweils 1 Mal die Varianten *dedičstvo* – ‚das Erbe‘, *oprávnený spoludedič* – ‚der begünstigte Miterbe‘ und *ona* – ‚sie‘). DeepL verwendete für die Übersetzung des Terminus *der Erbe* ins Slowakische zwei Varianten (98 Mal das Wort *dedič* – ‚der Erbe‘ und 31 Mal *dediča* – ‚des Erben‘). Bei der Übersetzung mittels Google Translate wurden drei Varianten festgestellt (100 Mal *dedič* – ‚der Erbe‘, 28 Mal *dediča* – ‚des Erben‘ und 1 Mal *poručiteľ* – ‚der Erblasser‘). Bei eTranslation wurden sogar fünf Varianten verwendet, um den Terminus (*der*) *Erbe* ins Slowakische zu übersetzen (91 Mal *dedič* – ‚der Erbe‘, 32 Mal *dediča* – ‚des Erben‘, je 2 Mal *dedičstvo* – ‚das Erbe‘ und *potomok* – ‚der Nachkomme‘ sowie 1 Mal *osoba* – ‚die Person‘).

Hinsichtlich der Genauigkeit der Übersetzung des Terminus (*der*) *Erbe* lieferten die untersuchten maschinellen Übersetzungstools ähnliche Ergebnisse, wobei Google Translate unter den eingesetzten Übersetzungstools am besten, eTranslation dagegen am schlechtesten abschneidet.

Der dritthäufigste Terminus im untersuchten Korpus ist (*das*) *Testament (závet)*, das in 55 von 763 Segmenten zu finden ist. Die maschinellen Übersetzungen dieses Terminus sind Tabelle 8 zu entnehmen.

Tab. 8: Vorkommen der maschinellen Übersetzungen von (*das*) *Testament*

Terminus technicus	ChatGPT	DeepL	Google Translate	eTranslation
<i>závet</i>	44	55	50	29
<i>testament</i>	4	0	0	0
<i>závetný</i>	3	0	0	0
<i>test</i>	1	0	0	0
<i>testamentový</i>	1	0	0	0
<i>závetie</i>	1	0	0	0
<i>vôľa</i>	0	0	3	20
<i>testamentárne</i>	0	0	1	0
<i>zákon</i>	0	0	0	3
<i>dedičstvo</i>	0	0	0	1
<i>spoločenstvo</i>	0	0	0	1

Bei der maschinellen Übersetzung des Terminus (*das*) *Testament* erwies sich DeepL als das zuverlässigste Tool, während eTranslation am wenigsten zuverlässig war.

Das Tool ChatGPT bietet sechs Varianten der Übersetzung von *Testament* an (44 Mal *závet* – ‚das Testament‘, 4 Mal *testament* – ‚das Testament‘, 3 Mal *závetný* – ‚testamentarisch‘ und jeweils 1 Mal *test* – ‚der Test‘, *testamentový* – ‚testamentarisch‘ und *testamentárne* – ‚testamentarisch‘). Das Tool DeepL erzielte in dem untersuchten Korpus eine hundertprozentige Übereinstimmung mit der menschlichen Übersetzung (55 Mal *závet* – ‚das Testament‘). Das Tool Google Translate bietet wiederum drei Varianten der Übersetzung an (50 Mal *závet* – ‚das Testament‘, 3 Mal *vôľa* – ‚der Wille‘ und 1 Mal *testamentárne* – ‚testamentarisch‘). Im Vergleich zu den anderen Tools war die Übereinstimmung der maschinellen und menschlichen Übersetzung von *Testament* durch eTranslation am geringsten. Dies mag daran liegen, dass beinahe die Hälfte der Vorkommen des Terminus *Testament* mit dem Wort *vôľa* („der Wille“) übersetzt wurde, das im Slowakischen ein umgangssprachlicher Ausdruck für *Testament* ist. Neben der Übersetzung *vôľa* bietet das eTranslation-Tool vier weitere Übersetzungsvarianten an (29 Mal *závet* – ‚das Testament‘, 3 Mal *zákon* – ‚das Gesetz‘ und jeweils 1 Mal *dedičstvo* – ‚das Erbe‘ und *spoločenstvo* – ‚die Gemeinschaft‘).

Die Übersetzung des Terminus (*der*) *Pflichttheil* (*povinný diel*), das in dem untersuchten Textkorpus am vierthäufigsten vorkommt, lieferte durchaus unterschiedliche Ergebnisse (die Schreibweise *Pflichttheil* folgt alten Rechtschreibregeln, deren sich der Autor des Entwurfs auch bei anderen Termini bedient). Der Terminus *Pflichttheil* findet sich in 50 der 763 Segmente (siehe Tabelle 9).

Tab. 9: Vorkommen der maschinellen Übersetzungen von *Pflichttheil*

Terminus technicus	ChatGPT	DeepL	Google Translate	eTranslation
<i>povinný dielo</i>	25	23	13	0
<i>zákonný dedičský podiel</i>	16	0	0	0
<i>dedičský podiel</i>	4	0	0	0
<i>povinný podiel</i>	3	8	20	0
<i>celkový povinný dielo</i>	1	0	0	0
<i>zákonný dedičský podie</i>	1	0	0	0
<i>podiel na záväzka</i>	0	4	0	0
<i>podiel povinnosť</i>	0	3	0	0
<i>podiel záväzka</i>	0	2	0	0
<i>podiel na povinnosť</i>	0	1	0	0
<i>podiel na dedičstvo</i>	0	1	0	0
<i>povinnosť</i>	0	1	1	35
<i>povinný časť</i>	0	1	14	5
<i>podiel</i>	0	0	1	0
<i>záväzok</i>	0	0	0	3
<i>povinný</i>	0	0	0	2

Terminus technicus	ChatGPT	DeepL	Google Translate	eTranslation
<i>byť to nutnosť</i>	0	0	0	1
<i>časť</i>	0	0	0	1
<i>záväzka</i>	0	0	0	1
<i>clo</i>	0	0	0	1

Das ChatGPT-Tool bietet sechs Übersetzungsvarianten des Terminus *Pflichttheil* (*povinný podiel*) (25 Mal *povinné dielo* – ‚pflichtiges Werk‘, 16 Mal *zákonný dedičský podiel* – ‚gesetzlicher Erbteil‘, 4 Mal *dedičský podiel* – ‚der Erbteil‘, 3 Mal *povinný podiel* – ‚der Pflichtteil‘ und jeweils 1 Mal *celkový povinný dielo* – ‚pflichtiges Gesamtwerk‘ und *zákonný dedičský podiel* – ‚gesetzlicher Erbteil‘). DeepL bietet neun Varianten (23 Mal *povinný dielo* – ‚pflichtiges Werk‘, 8 Mal *povinný podiel* – ‚der Pflichtteil‘, 4 Mal *podiel na záväzka* – ‚Anteil an Verbindlichkeit‘, 3 Mal *podiel povinnosť* – ‚Anteil Verpflichtung‘, 2 Mal *podiel záväzka* – ‚Anteil Verbindlichkeit‘ und jeweils 1 Mal *podiel na povinnosť* – ‚Anteil an der Verpflichtung‘, ‚Anteil am Erbe‘, ‚die Verpflichtung‘ und ‚pflichtige Teil‘). Google Translate verwendete fünf Varianten, um den Terminus *Pflichttheil* ins Slowakische zu übersetzen (13 Mal *povinný dielo* – ‚pflichtiges Werk‘, 20 Mal *povinný podiel* – ‚der Pflichtanteil‘, 14 Mal *povinný časť* – ‚pflichtige Teil‘ und jeweils 1 Mal *povinnosť* – ‚die Pflicht‘ und *podiel* – ‚der Anteil‘). Am wenigsten genau war das Tool eTranslation. Es bietet sogar acht Übersetzungsvarianten an (35 Mal *povinnosť* – ‚die Verpflichtung‘, 5 Mal *povinný časť* – ‚pflichtiger Teil‘, 3 Mal *záväzok* – ‚die Verbindlichkeit‘, 2 Mal *povinný* – ‚pflichtig‘ und jeweils 1 Mal *clo* – ‚der Zoll‘, *záväzka* – ‚die Verbindlichkeit‘, *časť* – ‚der Teil‘ und *byť to nutnosť* – ‚es sein Notwendigkeit‘).

Im Falle des Terminus *Pflichttheil* ist das korrekte slowakische Äquivalent *povinný podiel*. Da das Slowakische jedoch eine stark flektierende Sprache ist, für die die Flexion charakteristisch ist, nimmt auch die Zahl der grammatikalisch oft nicht korrekten Varianten der maschinellen Übersetzung zu. So werden beispielsweise *povinná časť* – ‚(der) Pflichtteil‘ und *povinný časť* – ‚der pflichtige Teil‘ als zwei verschiedene Übersetzungen eingestuft. Bei den maschinell erstellten Übersetzungen des Terminus *Pflichttheil* ist zugleich erkennbar, dass auch die Kongruenz zwischen dem grammatischen Geschlecht des Substantivs und der entsprechenden Endung des Adjektivs (abgesehen von der eigentlichen, nicht korrekten Übersetzung des Terminus) in der maschinellen Übersetzung aus dem Deutschen ins Slowakische oft nicht gegeben ist. So wurde beispielsweise *pflichtiges Gesamtwerk* als *celkový povinný dielo* übersetzt, wobei die Endung *-ý* im Slowakischen für die Deklination von Maskulina in der 1. Person Singular steht, das Substantiv *dielo* aber neutral ist und in der 1. Person Singular die Endung *-é* verlangt (somit *celkové povinné dielo*).

## 5 Diskussion

In der Diskussion liegt der Fokus darauf, die von den Übersetzungstools verwendeten Übersetzungsstrategien zu identifizieren. Vor allem geht es um diejenigen Strategien, die zu den nicht korrekten und juristisch nicht akzeptablen bzw. nicht bevorzugten Übersetzungslösungen geführt haben. Die einzelnen Varianten der maschinellen Übersetzungen werden aus Sicht ihrer Zulässigkeit und Verständlichkeit diskutiert. Anders gesagt geht es um die Antwort auf

die Frage, warum und wo die Maschine irrt. Dies wird an den 4 im Ausgangstext am häufigsten vorkommenden Termini veranschaulicht, die in zwei Gruppen geteilt werden können: *Gruppe 1: (der) Erblasser* mit 156 und *(der) Erbe* mit 131 Belegen im Ausgangstext und *Gruppe 2: (das) Testament* mit 55 und *(der) Pflichttheil* mit 50 Belegen im Ausgangstext. Die analysierten erbrechtlichen Termini können zugleich für die erbrechtliche Fachkommunikation als signifikant angesehen werden.

Im Allgemeinen wurden bei der maschinellen Übersetzung mittels DeepL (DL), Google Translate (GT), eTranslation (ET) sowie ChatGPT (GPT) drei Übersetzungsstrategien, die man als *Kompensationsstrategien* bezeichnen kann, angewandt. Die erste Strategie ist die *Beibehaltung des Begriffs* in der Ausgangssprache. Diese Strategie wurde nur bei zwei analysierten Termini festgestellt (*der Erblasser* und *das Testament*). Es ist fraglich, inwieweit diese Strategie bei der Rezeption des Zieltextes (der Übersetzung) hilfreich sein kann. Jedenfalls ist sie akzeptabler als Fehlübersetzungen, obwohl sie mit einem größeren Aufwand seitens der Rezipient:innen verbunden ist, die in einem solchen Fall in einem Wörterbuch nachschlagen müssen, wenn sie der Ausgangssprache nicht hinlänglich mächtig sind.

Diese Feststellung gilt vor allem für den Terminus *(der) Erblasser*, der von ChatGPT nicht übersetzt wurde. Dieser Terminus wurde sogar der slowakischen Grammatik durch Hinzufügung von Flexionsendungen angepasst, was befremdlich klingt und nicht akzeptabel ist (*Erblassera, Erblasserom*). Was den Terminus *(das) Testament* angeht, ist seine Rezeption nicht fraglich, da dieser Terminus im Slowakischen (aufgrund seiner Übernahme aus dem Lateinischen) durchaus verständlich und in einigen Situationen noch gebräuchlich ist, weshalb man hier nicht mit Rezeptionsschwierigkeiten rechnen muss. Einige Rechtswissenschaftler:innen bevorzugen jedoch statt *testament* den Ausdruck *závet* als Bezeichnung für letztwillige Verfügungen (Švecová 2010: 30, siehe methodologische Anmerkung zum Gebrauch der Termini *závet* und *testament*).

Die nächste Kompensationsstrategie bei der maschinellen Übersetzung könnte als *Verengung* bezeichnet werden. So wurden die Begriffe *(der) Erblasser* als *závetca, testátor* (‘Testator’) und *(der) Erbe* als *spoludedič* (‘der Miterbe’) ins Slowakische übersetzt. Dies ist jedoch streng juristisch nicht korrekt, weil der Begriff *Testator* enger definiert wird (als Erblasser gelten auch diejenigen Personen, die kein Testament erstellt haben; ihre Erben haben die Erbschaft aufgrund der gesetzlichen Erbfolge erworben).

Im Gegensatz dazu steht die *Generalisierung* (vgl. Kautz 2002: 131) als Kompensationsstrategie, die durchaus mit Rezeptionsschwierigkeiten (anderer Art) verbunden sein kann, da die Rezipient:innen die richtige Bedeutung erst mit Hilfe eines breiteren Kontexts erschließen müssen, wenn ihnen dies überhaupt gelingt. Als Beispiel für diese Strategie kann *vôľa* (‘der Wille’) genannt werden. Terminologisch korrekter ist jedoch die Bezeichnung *posledná vôľa*, auf Deutsch *der letzte Wille* (zur Synonymie der Bezeichnung *letztwillige Verfügung* siehe näher Švecová 2010: 30–38). Beim *Pflichttheil* (korrekte Übersetzung *povinný podiel*) handelt es sich um diese Belege (Generalisierungen): *podiel* (‘Anteil’), *podiel na zväzka* (‘Anteil an Verbindlichkeit’), *podiel povinnosť* (‘Anteil Verpflichtung’), *podiel zväzka* (‘Anteil Verbindlichkeit’), *podiel na povinnosť* (‘Anteil an der Verpflichtung’), *povinnosť* (‘Verpflichtung’). Aus diesen Beispielen geht eindeutig hervor, dass es sich hierbei um solche Begriffe handelt, die von ihrem Umfang her ein ziemlich breites Spektrum von Rechtsinhalten und Instituten decken. Darüber hinaus wurde bei den maschinellen Übersetzungen der Termini ins Slowakische häufig sowohl die Kongruenz als auch die Rektion verletzt.

Die Übersetzung von (*der*) *Erbe* als *oprávnený* („Berechtigter“) ist ein ähnlicher Fall. Die Ursache für Generalisierungen liegt darin, dass die Suche nach geeigneten Übersetzungslösungen auf der Textoberfläche geschieht. Die Übersetzungstools vergleichen nämlich große Datenmengen mit ähnlichen Kontexten und produzieren ihre Lösungen anhand von Oberflächenstrukturen. Aktuell sind sie offensichtlich noch nicht imstande, eine tiefere Begriffsanalyse durchzuführen (Begriffsinhalte und -umfänge zu vergleichen u. Ä.). Auf die Qualität der maschinellen Übersetzung kann natürlich auch das Volumen ähnlicher Texte Einfluss nehmen.

In dem untersuchten Korpus wurde jedoch auch eine Menge an Übersetzungslösungen identifiziert, die völlig falsch, irreführend und somit für die Rechtskommunikation nicht akzeptabel sind. Als Beispiele können folgende Lösungen angeführt werden: (*der*) *Erblasser* (*poručiteľ*) wurde als *dedič* („der Erbe“), *dedičstvo* („das Erbe“) oder *zanevretý* („der Gezürrnte“) übersetzt. Der Terminus (*der*) *Erbe* wurde sogar als *ona* (Pronomen *sie*), *das Testament* als *dedičstvo* („das Erbe“), *test* („Test“) oder *zákon* („Gesetz“) übersetzt.

Auch bei korrekten Übersetzungen der Termini hat es manchmal Fehler im Wortartenbereich gegeben, z. B. statt Substantiv (*závet*) hat ChatGPT den Terminus *Testament* als *závetný* oder *testamentárny* übersetzt („testamentarisch“), oder als *testamentárne* (Adjektiv bzw. Adverb). In einem Fall wurde es sogar in Form eines Substantivs übersetzt, das es in dieser Form im Slowakischen gar nicht gibt (*závetie*). Es handelt sich wahrscheinlich um ein neues Derivationsprodukt, das durch Hinzufügung einer Endung entstanden ist.

Zur Übersetzung des Begriffs *Erblasser* lässt sich noch anführen, dass in zwei Fällen auch eine Interferenz mit dem Tschechischen festgestellt wurde (*zostavitel* bzw. auch grammatisch nicht korrekt *zostaviteľ*; richtig *zůstavitel*). Als Derivation vom Verb *zanechat* („hinterlassen“) kann man ein „neues“ Wortbildungsprodukt *zanechávateľ* („Hinterlasser“) bezeichnen (in diesem Falle handelt es sich um die Derivation als Wortbildungsart, vgl. Vajičková 1996: 44–50), die zwar begrifflich aufgrund ihrer Motivation durchaus verständlich, terminologisch jedoch unzulässig ist. Terminologisch korrekter ist hingegen die Übersetzung dieses Terminus als *zomretý*, *zomrelý*, *zosnulý* („Verstorbener“), zumal der Begriff *Erblasser* in der Gesetzgebung aufgrund der Erbrechtsreform in Österreich von 2015 durch den Begriff *Verstorbener* oder *letztwillig Verfügender* ersetzt wurde. In der Rechtswissenschaft wird jedoch nach wie vor der Begriff *Erblasser* verwendet (Welser 2019: 7 f.).

## 6 Schlussfolgerungen

Wie bereits angeführt, müssen Übersetzungen im professionellen Kontext der Rechtskommunikation terminologisch korrekt und konsistent sowie rechtssicher sein. Wie die bisherigen Untersuchungen (einschließlich der hier besprochenen) zeigen, können diese Attribute von „unkontrollierten“ Maschinen (noch) nicht gewährleistet werden. Somit ist der Eingriff von fachlich kompetenten humanen Übersetzer:innen bei der endgültigen Beurteilung der Qualität von maschineller Übersetzung nach wie vor unabdingbar. Die maschinell erzeugten Outputs müssen zuerst geprüft und ggf. korrigiert und können erst dann freigegeben werden.

Die hier eingesetzten Übersetzungstools DeepL, Google Translate, eTranslation sowie ChatGPT brachten unterschiedliche terminologische Übersetzungslösungen, die aus juristischer Sicht mehr oder weniger akzeptabel bzw. korrekt sind. Generell sind sie jedoch noch nicht so ausgereift, dass sie imstande wären, spezifische Rechtsbegriffe der Ausgangssprache zu deuten und zu analysieren und dabei Tiefenstrukturen zu identifizieren, die dem jeweiligen Begriffssystem zugrunde liegen. Die von den Übersetzungstools verwendeten Kompen-

sationsstrategien helfen auch nicht immer, die Rechtsbegriffe richtig zu deuten, bzw. sie sind bezüglich der Rezeption nicht selten mit einem größeren (Zeit-)Aufwand verbunden. Beim Einsatz maschineller Übersetzung von Rechtstexten ist somit mit nachträglichen umfangreichen Korrekturen im terminologischen Bereich zu rechnen.

Der Vorteil sowie die Effektivität von Übersetzungstools besteht zurzeit vor allem in der Bereitstellung von bestimmten (aus ähnlichen Texten gewonnenen) Formulierungsmustern (Sätzen). Dies kann aus Zeitgründen vorteilhaft sein und kann eine gute Ausgangsbasis u. a. für das Post-Editing bilden. Bei der Beurteilung der Qualität maschinell erzeugter Übersetzungen ist im Allgemeinen auch unbedingt der Aspekt der Textsortenbestimmung, wie dies bereits in der Einleitung kurz angedeutet worden war, zu berücksichtigen.

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### Akronymverzeichnis

BLEU – Bilingual Evaluation Understudy (generative AI quality evaluation metric)  
CAT – Computer-assisted Translation  
DL – DeepL Translate  
EBG – Erster Entwurf des ungarischen Zivilgesetzbuches  
EMT – European Master's in Translation  
ET – eTranslation (machine translation service provided by the European Commission)  
GPT – ChatGPT (generative artificial intelligence chatbot)  
GT – Google Translate  
MT – Machine Translation  
TAUS – Translation Automation User Society

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# Do Translators Dream of Electric Brains?<sup>1</sup>

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**Abstract** Conceptual Metaphor Theory suggests that human thought is largely metaphorical, mapping concrete experiences onto abstract concepts. Translating is often understood through metaphors like *TRANSLATING IS BUILDING BRIDGES*, which shape how it is approached but fail to capture its full complexity. Similarly, the metaphor *THE BRAIN IS A COMPUTER* oversimplifies human cognition, ignoring its dynamic, adaptable, and context-dependent nature. Artificial neural networks, though loosely inspired by biological systems, rely on statistical patterns rather than genuine understanding. Large Language Models (LLMs) excel in producing fluent drafts but struggle with nuanced, context-dependent tasks. Misconceptions about AI capabilities often stem from oversimplified metaphors, fostering unrealistic expectations of replacing humans. Historical cycles of over-hyped machine translation breakthroughs highlight the persistence of such misconceptions. LLMs largely renew existing technologies rather than transforming the market. While they enhance translation workflows, they also increase reliance on the less rewarding post-editing work. Techno hype is also leading to declining translator enrollment and the closure of academic programs, even as market projections suggest strong growth. Despite these challenges, humans remain essential for managing ambiguity, integrating context, and making ethical decisions. Progress in multilectal communication and in AI would benefit from abandoning simplistic, binary views of humans versus machines.

**Keywords** artificial intelligence, brain-computer analogy, Grice's maxims, machine translation, situated cognition, translators' roles, Turing test

## Introduction

Conceptual Metaphor Theory (Lakoff/Johnson 1980) posits that much of human thought is fundamentally metaphorical. We map simpler, concrete experiences onto more complex or abstract ones that are difficult to understand or think through. For instance, the metaphor *TRANSLATING IS BUILDING BRIDGES* allows us to understand the complex concept of [TRANSLATION] through the concrete and more visual experience and notion of [BRIDGE CONSTRUCTION].<sup>2</sup> Expressions like *Her work spans multiple languages and cultures; Rabassa's versions*

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<sup>2</sup> This metaphor is ubiquitous in translation studies and it is also implicit in the works on translation by Wilhelm von Humboldt, Wolfgang von Goethe, José Ortega y Gasset, Roman Jakobson and Georg Steiner, to name but a few. In fact, it is etymologically ingrained in terms such as English *translate*, German *übersetzen*, Swedish *översättning* and Spanish *trasladar*, which are calques of *transfere* (participle

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brought García Márquez's works to English readers; and David Bellos' translations connected English-speaking economists to Piketty's analysis of wealth inequality illustrate how we often equate translating with building physical connections. We align the ideas of spanning distances and providing access, drawn from building physical structures, with the process of translation, and this influences how we think about communicative mediation and the flow of ideas across linguistic barriers.

This metaphorical structuring contributes to shape how we perceive and engage with the world, in that our scope and predictions in the complex domain are colored by what we think of the simpler domain. For instance, to examine how metaphors influence our understanding, Gentner/Gentner (1983) compared how people conceptualize electricity with two metaphors – ELECTRICITY IS FLOWING WATER and ELECTRICITY IS A CROWD OF MOVING PARTICLES – as they solved circuit problems involving batteries and switches. Participants primed with the FLOWING WATER metaphor viewed batteries as water tanks and switches as gates controlling flow. Those using the MOVING CROWD metaphor saw batteries as sources of motivated people and switches as turnstiles controlling crowd movement. The choice of metaphor significantly impacted the way participants reasoned about electrical circuits, and shows how metaphors shape cognitive strategies and influence problem-solving.<sup>3</sup>

Yet metaphors have their limitations. Some areas of experience resist metaphorical mapping or lack clear overlaps between domains. For example, the metaphor TRANSLATING IS TRANSFERRING MEANINGS is prevalent in discussions of translation, and works well in expressions like *She conveyed the message accurately* and *The meaning was lost in translation*. However, a statement like *The translator adjusted the cultural references for the target audience* cannot be easily expressed using that metaphor. This highlights the limitations of viewing [TRANSLATION] as a transfer of meaning from one language to another. There is no such transfer, and limitations in metaphorical mappings – like this one, where a metaphor fails to capture the target concept – are *blind spots* (*tote Winkel* or 'dead angles', Brünner 1987: 107) that can lead to comprehension gaps or misunderstandings. Blind spots underscore the limits of metaphorical thinking. While metaphors are powerful cognitive tools to make sense of complex ideas, they are not universally applicable, and certain aspects of reality remain stubbornly beyond their reach.

Metaphors can derive from other metaphors, and thus create layered conceptual structures. For example, TRANSLATING IS BUILDING BRIDGES builds on the metaphor TRANS-

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*translatum*, 'bring or carry over, transport, transfer'). The Latin term *traducere* that led to French *traduire*, Italian *tradurre* and Spanish *traducir* somewhat underscores agency but means pretty much the same: 'lead or carry across, cause to transfer'. It appears to have been first used in this sense by Notker Labeo Teutonicus (~950–1022) and was popularized by Leonardo Bruni in the Renaissance, superseding the term *interpretari* that also meant 'to explain or interpret'.

<sup>3</sup> While metaphors may ease our thinking towards adopting certain perspectives on aspects of reality, they do not determine how we engage with problems and ideas. We often use multiple, even conflicting metaphors for the same domain. For example, with [TIME] we use metaphors like TIME IS MONEY (*This meeting is a waste of time*), TIME IS A MOVING OBJECT (*Summer is coming up fast*), and TIME IS A CONTAINER (*He crammed everything into one hour*). Conversely, one metaphor can structure multiple domains: X IS A BUILDING shapes how we talk about an [ARGUMENT] (*Your argument is shaky*), a [RELATIONSHIP] (*We are building a future together*), and [KNOWLEDGE] (*She built her theory step by step*). These variations show our flexible and adaptive use of metaphors as optional lenses for tackling complex concepts.

LATING IS TRANSFERRING MEANINGS. The bridge metaphor not only suggests the transfer of meaning but also emphasizes the role of translating in facilitating understanding between people living in different realities and speaking different languages (“connecting cultures”), adding another layer of complexity to the idea of translation as transfer. Both metaphors, in turn, build on the conduit metaphor (Reddy 1979), which conceptualizes communicating as transferring ideas between people (or brains), as if traveling through a channel.

This provides a broader framework for understanding communication. Expressions like *Get your message across* or *This introduction is quite dense* reflect this way of thinking. However, such oversimplification can lead to misconceptions. How do these metaphors affect our understanding of translation? For example, they lead us to believe that meaning is an object that can be separated from the symbols that prompt humans to generate it; that meaning is measurable and can be preserved intact across languages; and that it can be universally grasped, regardless of individual factors such as knowledge, language proficiency, subject expertise, scenario, mood and the like.

In cognitive translation & interpreting studies (CTIS), these misconceptions about meaning and translation mirror those regarding *artificial intelligence* and *artificial neural networks*. Building on the notion of metaphorical limitations, I contend that these labels, both as theoretical and technical constructs, are rooted in the metaphor THE BRAIN IS A COMPUTER, which similarly constrains our understanding of the ongoing revolution in information and communication technologies (cf. also Muñoz 2016).<sup>4</sup> While this metaphor is useful in some scenarios, it misleads us by misrepresenting the nature, capabilities and limitations of these technologies. Just as the conduit metaphor oversimplifies the translation process, the computer metaphor supporting the notions of artificial intelligence and artificial neural networks can lead us to misunderstand and overestimate their role and potential impact on (professional) multilectal mediated communication.

### 1 Brain as computer

The BRAIN IS A COMPUTER metaphor draws parallels between our biological cognitive system and computing technology. The brain is analogized to computer hardware, while the mind represents the software (von Neumann 1958, Newell/Simon 1976). The central nervous system acts as a processor, working memory is likened to RAM, and long-term memory to hard drive storage. Both brain and computers process inputs: the former handles sensory and motor signals, while the latter manage digital inputs from devices like keyboards and cameras. Similarly, both of them yield outputs: brains control information processing and physical actions – such as making decisions and regulating heart rate – while computers generate information in various forms, like text or images.

The computer analogy offers an accessible framework for understanding cognitive functions. Yet, even if we ignore radical differences in both inputs and outputs, this view is significantly oversimplified and ignores fundamental differences between brains and digital systems

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<sup>4</sup> The analogy of brains as computers can be traced back at least to the works of Niels Steensen (1638–1686) and probably gained full scientific status with the posthumous publication of John von Neumann’s *The Computer and the Brain* (1958). Yet for many key figures in the first cognitive revolution, such as Allen Newell, Herbert A. Simon and Jerry Fodor, the brain-as-computer was not an analogy or metaphor – they believed they had discovered the actual nature of cognitive processes. Cf. also Richards (2018).

(review in Matassi/Martínez 2023). For instance, biological memory is far more sophisticated. Working memory and long-term memory may be similar in some respects to their computer counterparts, but computers store data sequentially and retrieve it as programmed, whereas the brain operates through a complex, dynamic network of electrochemical signals, with memories constantly interacting and reshaping based on new inputs, experiences and emotions. For example, when a computer searches for a word, it conducts a systematic, linear search through a database, comparing each entry until it finds a match, regardless of the context or prior usage. It is like using a sledgehammer to crack a nut. In contrast, words in our minds are interconnected through experience, emotions and contexts of use, along with other aspects. When searching for a word, humans might partially activate related concepts and synonyms, leading to more targeted and efficient retrieval processes that draw upon a rich web of associations. This allows for a nuanced understanding and contextual relevance that a straightforward algorithmic approach cannot achieve (Tulving 1972). Our brain's ability to encode, store and retrieve information is far more flexible; we update memories in response to changes, unlike the rigid, predetermined structure of computer memory systems, where data storage and retrieval are fixed. You have probably and painfully learned that, if a file in your computer becomes corrupted, the information is often irretrievable.

The first cognitive revolution's attempt to separate mind from brain, treating cognition as reproducible information processing, was necessary to develop artificial intelligence (AI) but, from a cognitive-situated perspective, it was fundamentally misguided (Bruner 1990). While this reductive misstep laid the groundwork for AI research, it also led to delusions about replicating human-like cognition in machines (e. g., Dreyfus 1992). The computational view reduced the embodied nature of human thought to abstract symbol manipulation, in a sort of revival of mind-body dualism (Searle 1980, Varela/Thompson/Rosch 1991). The human brain/mind system is vastly more complex, with capabilities that often surpass current computing technology. The brain excels in areas like adaptability, ambiguity resolution, uncertainty management and creative thinking (Epstein 2016). Emotions, intuition and consciousness are also integral to human cognition, and underscore the limitations of the computer metaphor (Damasio 1994, Colombetti 2014).

Recognizing these shortcomings, more recent approaches in cognitive science have shifted towards situated views (embodied, embedded, enactive, extended, affective), acknowledging the inseparable nature of mind, brain and body, and the limitations of computational models of mind (Clark 1997, Barsalou 1999). Still, the reduction of human thought to rational, conscious, self-contained problem-solving persists across disciplines and in the media, raising the critical question: "artificial what?" The next section explores how these narrow views on intelligence reshape our understanding of what it means to think.

## 2 Intelligence

Through factor analysis of academic performance across various disciplines, Spearman (1904) consistently observed positive correlations among several cognitive tasks. This led him to propose the existence of a general factor of intelligence, which he termed *g*. Spearman's concept of *g* went beyond specific knowledge, skills, or problem-solving strategies, and was thought to underlie performance across a wide range of cognitive domains, accounting for individual differences in intellectual ability. Spearman's theory of general intelligence opposed the idea that intelligence consists of unrelated abilities, and instead proposed a unified mental trait

influencing diverse cognitive tasks. This concept of *g* significantly shaped research and debates on how intelligence is or should be defined, measured and understood.

The idea of a single, quantifiable intelligence factor, though appealing in its simplicity, may not fully capture the complexity of human cognition (Sternberg 1985). The *g* factor is a useful psychological construct to study cognitive performance across domains, but it does not fully explain the complex, multifaceted nature of (human) intelligence. The Cattell-Horn-Carroll (CHC) theory of intelligence draws from Hebb's notions to distinguish between *fluid* intelligence (*Gf*), which involves problem-solving and reasoning, and *crystallized* intelligence (*Gc*), related to knowledge acquired through experience (Brown 2016). Wechsler's (2008) scale further reflects this complexity by assessing multiple aspects of intelligence, including verbal comprehension, perceptual reasoning, working memory and processing speed.

Traditional assessments, including Wechsler's, may tell us more about the conception of intelligence held by the tester than about the cognitive endowment of people tested. IQ tests and the concept of *g* fail to capture the emotional, social and adaptive features of intelligence, which vary across cultures and environments, challenging the idea of a universal cognitive measure (cf. Sternberg/Grigorenko 2004, Quesque et al. 2022). For example, a novice professional interpreter might excel in verbal skills and working memory – scoring high on traditional IQ tests – but struggle with the social abilities required to navigate cultural nuances in diplomatic settings.

Furthermore, the brain's plasticity and the role of environmental factors in cognitive development suggest that intelligence is not a fixed, innate quality, but a dynamic and evolving capacity. For example, a seasoned subtitler might excel in linguistic accuracy and cognitive flexibility – skills that would likely yield high scores in traditional IQ tests – but struggle with the adaptive ingenuity required when translating humor or idiomatic expressions. More than a century of research after Spearman's findings, the nature of intelligence remains elusive (Bartholomew 2004, Sternberg 2017). We still do not clearly understand what (human) intelligence is.

As for *artificial intelligence*, or *AI*, McCarthy (2007: 2) defined it as “the science and engineering of making intelligent machines, especially intelligent computer programs.”<sup>5</sup> AI is thus a branch of computer science focused on creating machines capable of performing tasks that typically require human intelligence (Chassignol et al. 2018: 17) – basically, machines that can learn from data and adjust to new situations. Still, when compared to human intelligence, *artificial intelligence* refers to the algorithms, machine learning models and neural networks that process data, recognize patterns, and make predictions. Hence, they execute tasks and functions traditionally requiring human cognitive skills – but they do so through fundamentally different mechanisms, and often yield different results.

Human intelligence is generally agreed to comprise many abilities and traits that current AI systems lack. While artificial intelligence can generate novel combinations from existing data, it lacks true *imagination* and *creativity* – the capacity to produce entirely new concepts

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<sup>5</sup> The term was first used by McCarthy et al. (1955) in the funding application for the famous Dartmouth Summer Research Project on Artificial Intelligence that would jump-start the field one year later. McCarthy chose the name partly to avoid narrower options such as *automata theory* and *cybernetics*. Samuel, Newell, and Simon did not like the term back then (Nilsson 2010: 78 f.). Interestingly, their objection at the time was to the word *artificial*, not *intelligence*. Here, *AI* will underscore the field, and *artificial intelligence* the digital imitation of human cognitive skills.

or valuable ideas without direct precedents (Boden 2004). Humans possess *intuition* – the ability to understand and make decisions without conscious reasoning. This trait, along with *dreaming* and *feeling*, which are uniquely human and animal characteristics, underscores the experiential gap between humans and machines.

Furthermore, human intelligence includes *consciousness*, *self-awareness* and subjective experiences that enable *metacognition*, or the ability to regulate and reflect upon one's own thinking processes (Damasio 1999). In the booth, experienced simultaneous interpreters often make split-second decisions about word choice or phrasing. This intuitive process, honed through years of practice, allows them to maintain the speakers tone and intent even when target language renderings cannot be exact. These aspects of human cognition are beyond AI's reach, whose limitations become more evident in complex communicative events, such as those that are multilectal and mediated (cf., e.g., Chen et al. 2023, Wang et al. 2025).

While artificial intelligence can work with programmed abstractions, it struggles with the flexible, *context-dependent abstract thinking* that humans perform naturally (cf. Brachman/Levesque 2004). Translators can often grasp allusions and abstract concepts, rendering them in the target language in original ways while somehow recreating the original's emotional impact. AI translation systems easily struggle with nuanced, context-dependent tasks, and often produce obvious renderings that, based on dictionary equivalents, may miss the text's inferred intent.

Humans make complex ethical decisions based on factors such as cultural norms, personal experiences and abstract principles. In contrast, AI systems can be programmed with ethical guidelines, but they lack the capacity for the kind of sophisticated *moral reasoning* that humans employ. *Learning* in artificial intelligence relies on vast datasets and statistical models, while in humans it is based on observations, experiences and education, and often needs few examples (“one-shot learning”). An interpreter can often quickly adapt to a speaker's unique accent, tone or speaking style after hearing just a few sentences. In contrast, AI speech recognition systems typically require extensive training data to accurately transcribe diverse accents and talking patterns (e.g., Awiszus et al. 2024, Huang et al. 2024).

Humans excel at multitasking and social interaction (cf. Chaminade et al. 2012). During a multilingual public speech, a consecutive interpreter listens to the speaker, takes down notes, translates the content mentally, speaks the translation, monitors her own output, and observes the speaker's and the audience's reactions to adjust her delivery accordingly. This complex interplay of cognitive and social skills remains challenging for artificial intelligence systems. Humans are also better at multi-sensory input and output, although current robots and self-driving cars use multiple devices – radars, lidars, accelerometers, microphones, etc. – to monitor various flows of information, aggregate them, and then make navigational decisions.

Despite these and other significant differences, sophisticated machine-learning algorithms and artificial neural networks developed in the 21st century have propelled AI forward. Artificial intelligence – as inferred from the outcomes of simulated aspects of human thought – excels at detached decision-making based on data, and at efficiency in specific tasks. Crucially, AI systems' remarkable speed in data processing and analysis may potentially offset many cognitive advantages that remain uniquely human. Such systems do not need motivation, and they never get tired. These remarkable strides, coupled with progress in natural language processing, have proven crucial for multilectal mediated communication. Artificial neural networks, in particular, are fundamental components powering machine translation systems and

voice recognition technologies. The next sections will explore the structure and function of biological and artificial neural networks.

### 3 Neural networks, biological

The brain coordinates functions like sensation, movement and cognition through a complex network of nerves that connect the body's sensors, muscles and glands with neurons as fundamental building blocks of the nervous system. All neurons in the human brain consist of (1) *dendrites*, which receive input from other neurons; (2) a cell body (*soma*), which maintains the neurons health, processes signals, and generates electrical impulses; and (3) an *axon*, a long fiber that transmits output signals. Communication between neurons occurs at (4) *synapses*, specialized junctions where the axon of one neuron connects to the dendrite of another.

Neurons communicate using electrical and chemical signals. The soma integrates chemical signals (*neurotransmitters*) from other neurons through the dendrites. If the input is strong enough, the soma fires internal electrical impulses (*action potentials*) that trigger the release of neurotransmitters at the axon terminals.<sup>6</sup> This affects neighboring neurons and creates multiple domino effects through many areas of the brain. Neurons use various neurotransmitters to either promote or suppress action potentials, creating a complex system of excitation and inhibition (Purves et al. 2018). This intricate balance allows for subtle information processing, much like how language processing requires weighing various linguistic elements such as syntax, semantics and co-text. The neuron's ability to modulate its response based on the strength and type of input is in some ways analogous to how machine translation systems consider co-textual cues and nuances to generate accurate and meaningful translations. But that is, at best, the *tertium comparationis*.

Each neuron can connect to thousands of others, and groups of interconnected neurons collaborate to perform specific functions, such as sensory perception and motor control. These *neural networks* can alter their connections based on experience, a process crucial for learning and memory. Neural synapses undergo constant modification throughout the day, with vast numbers of connections being strengthened, weakened, formed, or pruned. Adults continue to generate neurons, particularly in the hippocampus, a region crucial for memory and learning. Although the rate of new neuron formation is much higher during early development, our brain maintains this remarkable plasticity throughout life. It is constantly changing and self-regulating to adapt to environmental demands.

Neurons can belong to multiple networks simultaneously, and can send and receive signals within and outside their networks. This allows them to participate in several processes at once and across different scenarios. Additionally, multiple neurons can fulfill similar roles. This enables the network to keep working well despite the loss of some neurons, thereby providing fault tolerance. Neurons can fire at different times, and this enhances their ability to respond to changing conditions. Many neurons are in a resting state ("inactive") at any moment, so the active ones work more efficiently and reduce energy consumption.

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<sup>6</sup> The electrical signals of action potentials are too small and buried in background noise to be directly measured. Instead, techniques like EEG capture the summed electrical activity from large populations of neurons that mainly reflect excitatory and inhibitory postsynaptic potentials in the cerebral cortex, rather than the firing of individual action potentials. For an overview of EEG in CTIS research (cf. Hansen-Schirra 2017).

Consider how multilinguals process language. When hearing the word *book* in English, their brain might simultaneously activate related words in other known languages, like *libro* in Spanish. This reveals the brain's parallel processing capabilities (Rumelhart/Hinton/Williams 1986). If we cannot immediately recall the word in one language, we might access related concepts or synonyms, showcasing redundancy and fault tolerance. Furthermore, when we learn a new meaning or context of use for a word (like *to book a reservation*), we can integrate it without disrupting our existing linguistic knowledge, illustrating our brain's adaptability. These neural processes mirror challenges in machine translation, such as managing co-text, handling ambiguity and continuously updating language models.

In discussing memory, we mentioned activation and semi-activation of words. In neural terms, *semi-activation* means that some neural pathways associated with a word are engaged that allow related concepts or associations to emerge without fully retrieving the word itself. This can occur during processes like *priming* or when a word is partially recalled. The brain operates below the level of explicit symbols like words. It rather focuses on features and traits – like *cover, red, paper, chapters, novel, long* – and relies on sequences and combinations of neurons firing together, rather than discrete, self-contained representations in single neurons (Barsalou 1999). How a single word is processed illustrates the complexity of neural networks, because it activates multiple brain regions rather than relying on a single, isolated network. Broca's and Wernicke's areas in the left hemisphere handle speech production and comprehension, while memory-related areas, like the hippocampus, provide contextual information. When reading, visual areas in the occipital lobe recognize letters, and motor areas are activated for spoken words (Friederici 2011).

Motor areas play a dual role, for they execute actions and shape perception and understanding. Thinking about an action can activate the same motor pathways used to perform it, so cognition and physical embodiment are closely linked (Rolán et al. 2023). Understanding involves information cascading through multiple neural pathways, often impacting one other. Different neurons and circuits manage various aspects of a task simultaneously, enabling quick integration of information. This parallel processing allows the brain to handle multiple tasks at the same time – unlike computers, which often process information sequentially. The brain's ability to rewire itself, operate on minimal power – about 20 watts (Balasubramanian 2021) – and interact and adapt to the environment on the go also sets it apart from computers.

#### 4 Neural networks, artificial

Adrian's (1928) research demonstrated that neurons communicate through electrical impulses, inspiring efforts to model neural processes. Like *artificial intelligence*, the concept of artificial neural networks (ANNs) can be traced back to the 1956 Dartmouth Summer School (then dubbed *neuron nets*), grounded in Adrian's discoveries and the AI founders' exploration of constructing an "electronic brain."<sup>7</sup> Turing (1936) showed that all computational tasks could be described digitally. In 1950, he proposed his famous test for "machine intelligence" and argued that a machine could convincingly mimic human behavior – actually, verbal behavior in very stringent conditions. Other critical influences included Wiener's (1948) cybernetics, which examined control and stability in electrical systems, and Shannon's (1948) information

<sup>7</sup> Artificial Neural Networks were actually first conceptualized by Warren McCulloch and Walter Pitts in 1943, in an article often regarded as the starting point of ANN research.

theory, which formalized the digital signals essential for communication. Together, these ideas suggested that the brain's operations might be replicated with electronic circuits.

Early AI researchers split into two camps: those who sought to mirror human cognition and those who viewed that approach as limited, and favored practical problem-solving over mimicking the brain. Early machine translation systems followed the first approach and tried to replicate human rules for language processing, but soon struggled with the complexities of natural languages and their use. As the shortcomings of this approach became apparent, researchers shifted toward statistical methods, eventually leading to neural machine translation (NMT). At the core of NMT systems are ANNs – powerful statistical models that analyze large datasets and identify patterns in inputs such as language samples. The term *neural* is a somewhat misleading historical reference, as ANNs only loosely parallel biological neural systems in their structure and function (Rosenblatt 1958). Nonetheless, they do have some common structural traits and loosely-resembling functions that, albeit in a highly reduced manner, successfully emulate the brain's parallel processing, adaptability and fault tolerance.

ANNs consist of interconnected nodes, where each node is a mathematical equation that computes numerical inputs. These networks are typically organized into layers: (1) an input layer receives raw data; (2) hidden layers perform the actual processing to transform inputs into outputs by determining relationships within the data; then (3) an output layer generates the result or prediction. In the hidden layers, an *activation function* transforms inputs into outputs by determining whether each node should “fire” or be activated, based on the weighted sum of its inputs and on a constant numerical factor called *bias*, unique for each individual node, that shifts its activation threshold. The core of how ANNs work lies in the numerical values or *weights* assigned to connections between nodes, which determine how much influence one node's output has on another.

ANNs require weights to function, but they start as blank slates with no prior knowledge of the data they will encounter. Initially, the connections between their nodes are assigned random weights. As they analyze input data, ANNs systematically adjust the numerical values of weights and biases over time to minimize prediction errors through two main steps: a *forward pass*, where inputs are processed through the network to generate an output, and a *backward pass*, or *backpropagation*, where the prediction error is calculated and used to update the network's parameters (Rumelhart/Hinton/Williams 1986). This iterative process is known as *training*, and it allows ANNs to “learn” from the data they process. Over many iterations, or *epochs*, ANNs refine the accuracy of their predictions by continuously minimizing error through weight adjustments.

Different types of ANNs address specific needs. *Recurrent* neural networks (RNNs) were designed to handle sequential data and are especially useful for language translation and speech recognition. Now, *transformer* ANNs such as ChatGPT, Claude, and BERT – also known as *large language models* (LLMs) because they are trained with vast amounts of language data – have largely replaced RNNs in these tasks. Ten years ago, MT systems primarily used rule-based and statistical models that analyzed bilingual corpora for statistical relationships. By 2016, they began transitioning to neural machine translation. Today, most MT systems, such as DeepL, Amazon Translate, Google Translate and MS Translator, employ LLMs and handle tasks like summarization and text generation. Dedicated translation systems, like SYSTRAN and Apertium, are now rarer, while CAT tools (e. g., SDL Trados, memoQ, and Wordfast) have incorporated LLMs. So today, when we talk about MT systems, we are talking mostly about ANN-powered, transformer systems.

RNNs do not handle words as tokens or units. Instead, they represent them as continuous, high-dimensional vectors (actually, numerical representations), where similar words are mapped to nearby points in the vector space. These *embeddings* do not rely on fixed semantic features or sub-symbolic traits. Rather, they capture semantic relationships between words based on their usage and context and are learned through training on large datasets. RNNs process word vectors sequentially, while transformers do not. Instead, transformers encode word positions to account for their order and apply a *self-attention* mechanism that allows the model to assess relationships between all words in a sentence simultaneously, rather than one by one. This enables transformers to capture complex dependencies between words more effectively and process entire sequences in parallel, improving performance on tasks like language translation and text generation.

In other words, after analyzing word relationships, transformers also employ multi-head attention to focus on multiple words at once and feed-forward layers to refine their outputs and improve performance (Vaswani et al. 2017). The scope of operations is important and transformers often process text in chunks of a fixed size, typically defined by the number of tokens – a token can be as small as a character or as large as a word – that the model can handle in one go, called the *context window*. When a text exceeds this token limit, the transformer cannot process it all at once (Devlin et al. 2019, Liu et al. 2019). The context window for LLMs to process information used to be typically 512 or 1024 tokens, but the latest, more powerful LLMs reach 200,000 and counting, a truly astonishing achievement. This is not the way brains work, but it is a very sophisticated approach that yields quite good results in communication.

## 5 Transformers and brains

We described LLMs as applications of transformer ANNs trained with vast amounts of language data. This refers to the architecture and the size of the training dataset, but a third element significantly impacts their performance: the conversational agent that users interact with. While the LLM handles the heavy lifting of language processing, the conversational agent manages the dialogue as an HCI interface with the LLM. There is often a significant gap between what transformer models can technically do and how they can be made to perform specific tasks effectively – that is why *prompting* has become a buzzword that hardly needs explanation. Let us first address transformers, then their chatbots.

While transformers brought about substantial enhancements in processing efficiency, from a cognitive perspective they are not fundamentally different from RNNs. Both operate on mathematical principles and pattern recognition, and they differ from human neural networks in similar ways (Lake et al. 2017). ANNs have a limited number of nodes and layers, and predefined architectures that restrict their flexibility and generalization capabilities. The large version of BERT had 24 transformer layers and ChatGPT 3 had 96. In contrast, the human brain has about 86–100 billion neurons, and each neuron has thousands of synaptic connections with other neurons, within and across “layers”.<sup>8</sup> The dense and intricate mesh of white matter connections in the brain allows us to view it as a single, complex neural network.

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<sup>8</sup> The human brain has regions and structures, such as the *cortex*, *subcortex*, and *cerebellum*, each with different types of neurons that serve distinct functions. Some aspects of brain function, like sensory processing areas, relay information through successive stages, which enables their description as working in layers, but these aspects are the closest the brain comes to having a layered organization.

These differences explain why a human translator can convey the tone and style of a 16th-century book dedication more accurately than an ANN tool trained on modern text, which may produce jarring translations. ANNs typically rely on large datasets and statistical patterns, so they are prone to overfitting and unable to grasp subtleties. Interpreters may quickly adapt legal terminology when translating between different countries legal systems, but ANN-based legal translation tools might struggle with cross-system interpretations, potentially mistranslating key legal concepts.

Human brains are robust to noisy or incomplete information, and can often fill in gaps or make sense of unclear inputs, while ANNs can underperform when facing noise in the data. This limitation underscores challenges in practical applications like translating. Humans can easily translate handwritten notes with smudges or crossed-out words, while an ANN-based optical character recognition system might produce significant errors when processing the same document. During an international video conference with poor audio quality, a human interpreter can still accurately convey a message by inferring meaning from context and visual cues. An ANN-powered automated captioning system might produce a garbled, inaccurate transcript due to audio interference.

Like all AI applications, transformers depend on statistical correlations, not on understanding, and this may result in rough translations. When translating patient consent forms, a transformer may generate a technically correct output that fails to convey the urgency or importance of certain medical procedures. Their lack of real-world knowledge can result in outdated responses or ignorance of recent events (cf. Marcus/Davis 2020), which can only worsen over time. Most transformers and other AI systems rely heavily on their training datasets, making their static knowledge increasingly outdated over time. Retraining them, however, is unlikely to fully satisfy anyone's particular needs, precisely because of the one-size-fits-all approach at the core of their development.<sup>9</sup>

When translating a corporate sustainability report, a transformer may not recognize recent developments in environmental legislation, global sustainability initiatives or even public opinion. These systems can also produce biased or offensive content based on their training data (Gallegos et al. 2024, Resnik 2024). For instance, in 2016 Microsoft launched Tay, an artificial intelligence chatbot that quickly learned from interactions with Twitter users and had to be immediately removed because, within hours, it began to produce racist, misogynist, and fascist tweets, reflecting the toxic language it encountered (Wolf/Miller/Grodzinsky 2017).<sup>10</sup>

ANNs can produce fragmented or incomplete translations of long passages (Wang et al. 2024) because, even though their context window may be impressively large, mechanisms like "attention" lead them to focus on local features and contents as they weigh the importance of specific words or phrases in relation to others. Their reliance on immediate co-text explains why they may mishandle ambiguity and polysemy when faced with unclear or limited context (Wang/Wang/Fujita 2020, Peng/Bawden/Yvon 2024). For instance, within the same long legal document, the word *settlement* could sometimes refer to a financial agreement to close a dis-

<sup>9</sup> Personalized applications, such as company chatbots and recommender systems, are resource-intensive and often invasive, and still not flexible or precise enough. Domain-specific models, such as Watson Health, CoCounsel and AlphaSense, show more promise precisely because they distance themselves from artificial *general* intelligence.

<sup>10</sup> For an overview raising ethical issues and dilemmas associated with the deployment of AI, cf. Bird et al. (2020).

pute and other times to the act of concluding a lawsuit, a difference that transformers might miss.

Finally, transformers lack explicit goals, intentions and perspectives on texts, their uses and their users. Rather than engaging in communication with language as individuals do, they mimic patterns derived from large social common denominators. In other words, everything that most people do will be picked up by LLMs, even if it is incorrect. LLMs undergo further training from user interactions, meaning their new input is often more varied and flawed than the original, curated training dataset. LLM biases go well beyond erred social stereotypes (reviews in Ferrara 2024, Xue et al. 2024). Users personify LLMs and tend to forget that there is nobody there (Guingrich/Graziano 2024), partly because chatbots are intentionally trained to misleadingly impersonate humans. This brings us to the particular problems that LLM chatbots pose.

LLM chatbots often fail to keep conversational flow and maintain coherent common grounds across several turns. They struggle with at least four fundamental limitations that undermine their conversational abilities: lack of genuine understanding, constrained memory capacity, absence of goal-directed behavior, and inherent biases. Let us consider some illustrative exchanges of my own interaction with ChatGPT 3.5 – the first LLM I used, and the most popular until 2024. First, LLMs process language through statistical patterns, they do not really understand it. Without real-world experience or embodied cognition, they produce responses that sound plausible but may be erred or untrue:

- [1] User – Translate **Se les cayó el alma a los pies** into English.  
 LLM – *Their soul fell to their feet.*  
 User – That’s literal. What does it mean?  
 LLM – *It means **they were disheartened**—similar to **their heart sank**.*  
 User – So why didn’t you translate it that way first?  
 LLM – *You’re right. I should have translated the meaning rather than the words. **Their heart sank** or **they were devastated** would be better translations.*

Second, LLMs suffer from severe memory constraints. They disproportionately focus on recent inputs and progressively forget earlier conversation parts. This leads to redundant questions, contradictions, and losing their track. Techniques like summarization help, but maintaining coherent memory across conversations remains a challenge.

- [2] User – What’s more casual in English **keep me posted** or **keep me in the loop**?  
 LLM – *In English you can say:*
- *Let me know*
  - *Give me a heads up*
  - *Fill me in*
  - *Keep me updated*
  - *Touch base*
- User – No, just compare those two specific phrases.  
 LLM – *There are many situations where you might want to inform someone:*
- *Drop me a line*
  - *Keep me posted*
  - *Shoot me a message*
- User – Stop! Just tell me which is more casual between **posted** and **in the loop**.  
 LLM – ***Keep me updated** has a more formal or professional tone.*

Third, LLMs lack goal-directed behavior. As reactive systems, they respond to immediate prompts without maintaining consistent objectives. This results in abandoned tasks, lost focus, and poor handling of multiple requests. While workarounds exist, the core problem persists: LLMs cannot independently maintain direction across extended interactions or manage complex, multi-step processes.

- [3] User – I need to translate this business letter to Spanish. It should be formal, use business terminology, and keep product names in English.
- LLM – *I'll help you with that. Please share the letter.*
- User – Dear stakeholders, I am pleased to announce that PowerSuite 3.0 will launch next quarter, bringing unprecedented features to our enterprise solutions.
- LLM – *Estimados accionistas: Me complace anunciar que PowerSuite 3.0 será lanzado el próximo trimestre, aportando características sin precedentes a nuestras soluciones empresariales.*
- User – Here's the second sentence: The integration with CloudConnect will enhance productivity across all departments.
- LLM – *La integración con **ConectorNube** mejorará la productividad en todos los departamentos.*
- User – You translated **CloudConnect** when it should stay in English
- LLM – *Disculpe. La integración con CloudConnect mejorará **tu** productividad en todos los departamentos.*
- User – Now you switched to informal **tu** instead of formal [usted]
- LLM – *La integración con CloudConnect mejorará su productividad en las diferentes **áreas**.*
- User – Why did you change **departments** to **areas**? That's less formal
- LLM – *La integración con CloudConnect mejorará su productividad en los departamentos y **secciones operativas**.*

Finally, as mentioned, LLMs inherit and amplify biases from their training data. Beyond cases like Microsofts Tay's radical, offensive political and social slurs, subtle biases affect LLMs' information quality and knowledge representation. They tend toward outdated views and oversimplified answers, avoiding nuanced engagement with complex topics. Current debiasing efforts offer incremental improvements but no fundamental solutions.

- [4] User – How does our brain store and access words?
- LLM – *The mental lexicon functions like an internal dictionary, where words are stored in hierarchical networks. When we need a word, we access this dictionary through spreading activation.*
- User – That's a rather old model from the 1970s.
- LLM – *Modern research shows distributed neural networks process lexical information through dynamic patterns of activation across brain regions.*
- User – So why did you start with the mental lexicon model?
- LLM – *The mental dictionary model helps explain how we store and retrieve words, while neural networks demonstrate the actual brain mechanisms behind lexical processing.*
- User – Those are contradictory explanations.

- LLM – *Words are organized in our mental lexicon which operates through distributed neural pathways in the temporal and frontal regions, combining storage and processing functions.*
- User – You're still mixing old cognitive models with current neuroscience.
- LLM – *Distributed neural networks process lexical information through dynamic activation patterns in interconnected brain regions, while maintaining a hierarchical organization similar to a mental dictionary.*

These inconsistencies frustrate users who expect a seamless conversation and they undermine their trust in the tool. In addition, chatbots may hide that LLMs did not successfully execute complex instructions, sometimes overlooking key components or failing to fulfill detailed requests. Often, prompts that would be even unnecessarily explicit for humans are inaccurate and ambiguous for chatbots (Wang/Wang/Fujita 2020). In a way, prompting is the new pre-editing.

Misunderstandings by chatbots may lead LLMs to generate redundant information and provide irrelevant, inappropriate and even false replies, especially in complex discussions (Shi et al. 2023). A translator seeking clarification on a specific idiomatic expression might receive multiple unrelated examples instead of targeted responses, diminishing the chatbots utility:

- [5] User – How would you translate “no tiene pelos en la lengua”?
- LLM – *Here are some English expressions about speaking directly:*
- *Speak your mind*
  - *Tell it like it is*
  - *Call a spade a spade*
  - *Get straight to the point*
  - *Be upfront*
- User – Which one matches the Spanish expression?
- LLM – *When talking about honest people we can say:*
- *Wear your heart on your sleeve*
  - *Give it to you straight*
  - *Put all cards on the table*
  - *Say what you mean*
- User – Please just translate “no tiene pelos en la lengua”.
- LLM – *The expression means being direct, like:*
- *Not beat around the bush*
  - *Not mince words*
  - *Not hold back*
- User – Just give me ONE equivalent phrase
- LLM – *Not to mince words is the closest match, as it captures the same meaning of speaking directly without restraint or filters.*

*Hallucinations* – plausible yet nonsensical output – in LLMs are structural. They stem from probabilistic predictions rather than factual accuracy, incomplete training data, ambiguous or incomplete queries, and prioritizing user satisfaction over truthfulness (Huang et al. 2023, Xu/Jain/Kankanhall 2024). In brief, LLM chatbots have several technical problems that may also be addressed from a communicative perspective. LLM chatbots frequently fail to meet users' expectations regarding the quality, quantity, relevance, and manner of their contributions to

the ongoing communicative exchange. That is, often LLM chatbots do not consistently make their contribution such as is required, at the stage at which it occurs, by the accepted purpose or direction of the talk exchange in which they are engaged, as humans usually do (Grice 1975). In clearly deviating from human behavior, they thus fail to pass the Turing test.

## 6 A reality check by way of conclusion: human translation and AI

From what we have seen, we cannot know whether artificial intelligence truly exists, as we do not yet fully understand what intelligence is. In any case, human intelligence may be a fuzzy concept but it is definitely much broader than artificial intelligence. Furthermore, both intelligence and neural networks differ considerably between humans and computers. The latter do not accumulate situated knowledge and life experience, which are integral to human mental abilities and behavior. Self-awareness is also absent in machines, and they cannot adapt beyond their training data. They operate in a disembodied realm without the physical interactions that shape human cognition (Glenberg/Jones 2023).

Likewise, the way computers process natural languages is not the way we humans do it, and artificial neural networks (ANNs) share only a small, distant resemblance to our brain's biological structures. AI-powered systems, though inspired by human processes, function differently from their biological counterparts. ANNs are stochastic parrots that do not understand language (Bender et al. 2021, Choudhury/Rogers/Augenstein 2022) – and lack intuitive, situated understanding and flexible reasoning.

But why should that matter? Biomimicry is not about copying nature exactly; rather, it serves as a springboard for innovation. Evolutionary solutions inspire us but are not necessarily the best designs for machines. This principle can be seen in how trains and planes evolved from observing birds and animals. Trains do not imitate the muscles of animals; planes do not flap their wings like birds. Instead, engineers derived and adapted principles of movement and flight to create entirely new modes of transportation optimized for their use.

Similarly, the divergences between artificial and human intelligence, between biological and artificial neural networks, show that biomimicry can inspire innovation without being a direct model, let alone a blueprint, for replicating human traits and skills. The goal is not to create perfect copies of natural features but to abstract principles that lead to better solutions for specific human problems. Of course, this would be irrelevant were it not for the fact that laypeople and professionals alike unwittingly deceive themselves into thinking that AI systems are akin to people, influenced by this metaphorical analogy to human intelligence (cf. Floridi/Chiriatti 2020, Poivet et al. 2023). This misconception feeds into the problematic relationship between professional translators and AI tools, where the boundaries between human expertise and machine-enhanced performance blur.

In sum, machines do not think the way we do, they do not understand language, and they do not translate – at least, not in the way we can and do. Despite these challenges, LLMs offer strong support to translators. They generate fluent, coherent drafts that are often more readable and contextually appropriate than those produced by NMT systems. LLMs effectively apply syntactical and grammatical rules in both source and target languages, handle colloquial and idiomatic expressions well, maintain consistent terminology – and they work fast. AI does offer potential to reduce workload, particularly for routine tasks.

Nevertheless, the idea that AI systems could completely replace human translators in producing high-quality translations is fundamentally flawed. No organization or individual with a

serious stake in their communication would risk publishing a text or communicative product without human oversight. Furthermore, the projection that translators will become engineers controlling automated processes is unrealistic and will likely affect only a small portion of an enlarged market. Misunderstanding AI could result in the premature replacement of human expertise in areas where it is irreplaceable. These reflections bring us to the current state of professional translation and its evolving relationship with AI systems.

## 7 Epilogue: AI systems in professional translation

In 1954, the Georgetown-IBM experiment demonstrated an MT system translating 60 Russian sentences into English, and a few researchers rushed to claim that fully automatic, high-quality translation would be achieved within a few years. By the 1980s, companies introduced rule-based MT systems like SYSTRAN, arguing they were capable of addressing all translation needs for businesses. Soon it was obvious they did not. In the 1990s, translation memories (TM) emerged, offering efficiency for repetitive texts, but they still required human input for creative or complex tasks. The late 2010s saw the rise of neural networks and neural machine translation (NMT) systems like DeepL, which significantly improved fluency and accuracy. Each of these waves was accompanied by claims that human translation would become obsolete.

Now, it is the turn of large language models (LLMs). While they represent a major technological leap, their capabilities are often overestimated. Misconceptions about their potential have fostered unrealistic expectations of replacing human translators. Paraphrasing Mark Twain, the report of human translation's death is an exaggeration. With the accelerated development of LLMs, a majority of translation *scholars* expect MT to be employed in most translation tasks by 2030 (ELIS 2023: 37). However, the growth of LLMs largely reflects a renewal of existing technologies rather than carving out a new sector or chipping away at the work of human translators. Mediators who relied on free or low-cost MT tools are transitioning to LLM-based solutions, but this is unlikely to decrease the proportion of human translation within the steadily growing language services market.

Meanwhile, at the 2024 AMTA conference in Chicago, prominent figures already started tempering the current LLM hype, emphasizing that AI tools are valuable to enhance mediators' capabilities while the core of translating remains a deeply human endeavor. It is just becoming a different core, in ways we cannot really foresee. Professionals increasingly find themselves in a collaborative role with AI, using machine-generated drafts as a starting point for technical manuals or other standardized content. Slator (2024) reports that, in 2023, two-thirds of professional translators had used AI tools in their work over the prior 12 months – but mainly for translation drafting, not for post-editing. Almost one-third also used AI to generate alternatives, while fewer than one in seven applied it for tasks such as adjusting tone, register, or style; proofreading; or improving fuzzy matches. Only one in ten used AI for maintaining consistency in terms and style or for creating and refining glossaries. Lesser applications included summarizing texts, estimating translation quality, and analyzing source texts (Slator 2024).

The fear of missing out on new technologies has led to hasty adoption of the last trendy tools, often at the expense of translators' working conditions (Muñoz 2022). While these tools enhance productivity, they have coincided with an increased reliance on less rewarding post-editing work. According to ELIS (2024: 8, 47), most professionals view the language

industry as a decent work environment, and more than two-thirds of new freelancers believe they can sustain themselves in it. In contrast, experienced professionals report declining incomes linked to inadequate compensation for post-editing. They perceive that the dominance of large language companies compels them to accept lower-paying work, which adversely affects their work-life balance (ELIS 2024: 23). Small wonder that today's translators don't dream of electric brains.

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