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# Some Reflections on the Interface between Machine Translation Literacy and Data Literacy

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## Abstract

Due to the widespread use of data-driven neural machine translation, both by professional translators and layperson users, an adequate *machine translation literacy* on the part of the users of this technology is becoming more and more important. At the same time, the increasing datafication of both the private and the business sphere requires an adequate *data literacy* in modern society. The present article takes a closer look at machine translation literacy and data literacy and investigates the interface between the two concepts.

## keywords

digitisation, datafication, translation industry, neural machine translation, machine translation literacy, data literacy

## INTRODUCTION

Like many other industries, the translation industry has undergone an accelerating process of digitisation and datafication in recent years [Sandrini, 2017].<sup>1</sup> A high-performing translation technology based on the interplay of digitisation and datafication is the data-driven architecture of neural machine translation (NMT), which is having a disruptive effect on the translation industry [ELIS, 2021]. Given the high relevance of NMT both in the field of professional translation and in wider society, where this technology is increasingly used by laypersons as an aid to understand foreign-language content, [Bowker and Ciro, 2019] call for developing an adequate *machine translation (MT) literacy*, both in professional translators and in layperson users. Of course, an increasing digitisation and datafication cannot only be observed in the translation industry and other professional sectors but in all layers of modern society, which requires an adequately educated citizenry. One of the many initiatives that have been established in this context is the European Union's *Digital Competence Framework 2.0* [European Union, 2019; see also O'Brien and Ehrensberger Dow, 2020: 148], which specifies key components of digital competence in five areas (1. information and data literacy; 2. communication and collaboration; 3. digital content creation; 4. safety; 5. problem-solving). Parallel to this extensive EU framework, which covers a wide range of digital competencies, there are various more targeted initiatives focusing on individual competencies. One area with particular relevance is *data literacy* (see area 1 of the EU's Digital Competence Framework), since, inter alia, the accumulation of large volumes of (high-quality) digital training data is one of the crucial factors contributing to recent advances in artificial intelligence (AI) research and modern societies rely heavily on data-based decision making.<sup>2</sup> In this context, [Ridsdale et al., 2015: 2] claim that data literacy is "an essential ability required in the global knowledge-based community" and that "any country that does not have a technology and data-savvy citizenry will ultimately be left behind both socially and economically" [ibid.: 8]. Given the concurrent

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<sup>1</sup> At the same time, translation studies hat undergone a *technological turn* which, according to [Jiménez-Crespo, 2020], has been completed by now.

<sup>2</sup> In this context, see the seminal paper by [Halevy, Norvig and Pereira, 2009] on *The Unreasonable Effectiveness of Data*.

rise in prominence and the high relevance of MT literacy and data literacy, the current article will take a closer look at these two concepts and explore their interface.

## 1 MT LITERACY

According to [O'Brien and Ehrensberger-Dow, 2020: 146], "MT literacy means knowing how MT works, how it can be useful in a particular context, and what the implications are of using MT for specific communicative needs". [Bowker, 2021a: 26] points out that MT literacy is not a static but rather a dynamic concept, which can be adapted according to the needs of individual target audiences. Recent work on MT literacy has stressed the overall societal relevance of this concept beyond professional translation [Bowker and Ciro, 2019: 35] and hence tended to focus on MT literacy requirements of layperson audiences such as the scholarly community [Bowker and Ciro, 2019] or students (and teachers) of non-translation specific undergraduate university programmes [Bowker, 2021b]. The present article takes a step back from this wide conception of MT literacy and focuses on *professional MT literacy*, which is understood here as the full range of MT-related competencies professional translators may require in order to participate successfully in the various phases of the MT-assisted professional translation process (for a recent overview of this process, see [Krüger, 2019]). Figure 1 below depicts a rough outline of a 5-dimensional MT literacy model, which is based on the analysis of relevant MT literature in the field. The model merely serves to provide structure to the following discussion and is not intended to be a fully-fledged MT literacy/competence model.

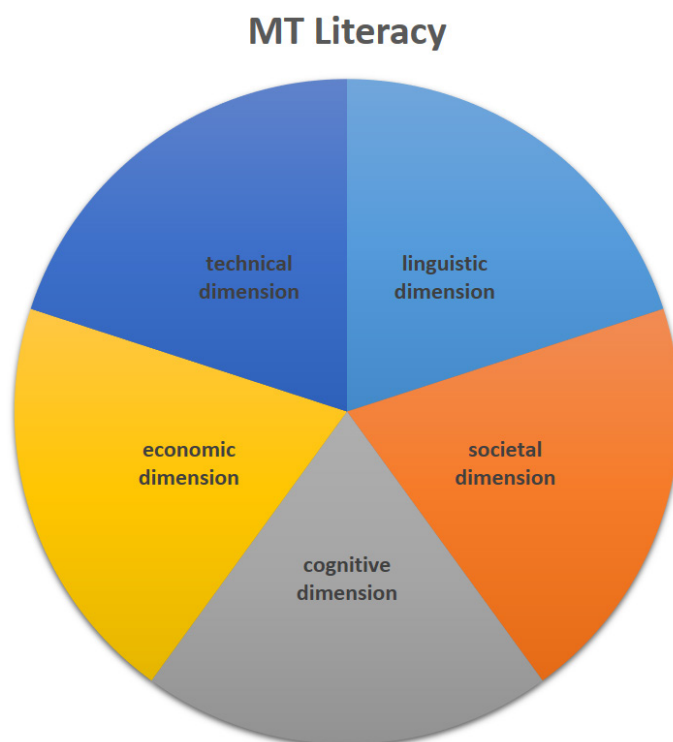


Figure 1. Outline of a 5-dimensional MT literacy model

The following sections will provide a more detailed overview of the five proposed dimensions of MT literacy. Owing to space limitations, the overview will be only cursory and fragmented (although references to more detailed sources will be given) and it will disregard the multitude of interrelations between the individual dimensions of MT literacy.

### 1.1 Technical dimension

The technical dimension of MT literacy is concerned with knowledge about:

- 1) *the technical basics of (primarily) NMT* (word embeddings, basic NMT architectures such as recurrent neural networks and transformers, etc. [Koehn, 2020]),
- 2) *extensions to NMT architectures* (e.g., adaptive and interactive MT [Daems and Macken, 2019], document-level MT [Maruf, Saleh and Haffari, 2021] and multimodal MT [Sulubacak et al., 2020]),
- 3) *MT training pipelines* (selecting/compiling/organising/cleaning training data, creating subword vocabularies and converting training data into subword units, splitting the data into training/development/test sets, etc. [Buj et al., 2020]),
- 4) *methods for NMT domain adaptation* (including terminology integration [Saunders, 2021]),
- 5) *automatic metrics for MT quality estimation/evaluation* [Specia, Raj and Turchi, 2010],
- 6) *integrating NMT systems into translation workflows/systems* (APIs/connectors, usability/ergonomics, data security, etc. [Cannavina, 2018; Koehn and Wiggins, 2021]),  
etc.

### 1.2 Linguistic dimension

This dimension is concerned with knowledge about:

- 1) *pre-editing texts for MT* (including knowledge about controlled languages and translation-oriented authoring [Marzouk and Hansen-Schirra, 2019]),
- 2) *post-editing MT output* (including knowledge about different post-editing (PE) levels such as light and full PE, about relevant standards/guidelines [ISO 18587, 2017], about negative translatability indicators and typical error patterns of NMT [Way, 2018]),
- 3) *quality expectations for generic/domain-adapted MT systems when translating particular domains/genres* [Koehn and Wiggins, 2021],
- 4) *manual MT quality evaluation* (adequacy/fluency assessments, relevant error typologies, etc. [Rivera-Trigueros, 2021]),
- 5) *linguistic quality requirements for MT training data* [Koehn and Wiggins, 2021],  
etc.

### 1.3 Economic dimension

This dimension is concerned with knowledge about:

- 1) *methods for estimating/measuring the effort involved in machine translation post-editing (MTPE)* [Daems et al., 2017],
- 2) *methods for price calculation in MTPE* [TAUS, 2013],
- 3) *feasible productivity gains in MTPE* [Macken, Prou and Tezcan, 2020],
- 4) *how business processes can be set-up/optimised for MT integration* [Cannavina, 2018; Koehn and Wiggins, 2021],
- 5) *potential business risks associated with using MT systems* (including the use of MT for texts pertaining to safety-critical domains, issues of liability/data security, etc. [Canfora and Ottmann, 2020]),  
etc.

### 1.4 Societal dimension

This dimension is concerned with knowledge about:

- 1) *ethical aspects of MT* (including knowledge about the crucial role of human translators in providing high-quality MT training data, about copyright issues, data ownership/dispossession, etc. [Moorkens et al., 2016])
- 2) *MT-induced changes in the public perception/industry-internal role of human translators* (potential translator marginalisation/disempowerment, etc. [Moorkens et al., 2016; Sakamoto, 2019]),
- 3) *potential biases in MT systems* (gender bias, etc. [Saunders and Byrne, 2020]),

etc.

### 1.5 Cognitive dimension

This dimension is concerned with knowledge about:

- 1) *factors potentially increasing cognitive load in MTPE* [Daems et al., 2017],
  - 2) *changes in text-receptive/text-productive processes in human translation vs. MTPE* [Krüger, 2018],
  - 3) *potential semantic/syntactic/stylistic MT priming effects* [Toral, 2019],
- etc.

Individual aspects of the MT literacy dimensions sketched above will be discussed in more detail in section 3 concerned with the interface between MT literacy and data literacy.

## II DATA LITERACY

Given the high societal relevance of data literacy as discussed briefly in the introductory section, it is not surprising that there exist a plethora of data literacy definitions and initiatives promoting the development of this literacy in modern societies (for an overview, see [Misra, 2021]). While there is no generally accepted definition yet, there seems to be a consensus that data literacy overlaps, to some extent, with literacies such as information literacy and statistical literacy [Ridsdale et al., 2015: 8; Misra, 2021: 5].<sup>3</sup> At the same time, the relevant literature stresses that data literacy comprises not merely a set of technical skills associated with data science, analytics or statistics but that it also involves critically thinking about and handling data in different contexts [Misra, 2021: 7].<sup>4</sup>

The current discussion will be based on the approach to data literacy developed by [Ridsdale et al., 2015], since this approach has been widely adopted and forms the basis of a range of data literacy initiatives and because the definition proposed by the authors is a synthesis of other existing definitions of data literacy and is both fine-grained and at the same time wide enough to be applicable to a wide range of contexts. According to [Ridsdale et al., 2015: 11], data literacy is “the ability to collect, manage, evaluate, and apply data, in a critical manner”. Based on this definition and a survey of the relevant literature on data literacy, the authors developed a *Data Literacy Competencies Matrix* (DLCM), which is depicted in figure 2 below:

Conceptual Framework		Data Collection				Data Management											
Introduction to Data		Data Discovery and Collection		Evaluating and Ensuring Quality of Data and Sources		Data Organization		Data Manipulation		Data Conversion (from format to format)		Metadata Creation and Use		Data Curation, Security, and Re-Use		Data Preservation	
Data Evaluation										Data Application							
Data Tools	Basic Data Analysis	Data Interpretation (Understanding Data)	Identifying Problems (Using Data)	Data Visualization	Presenting Data (Verbally)	Data Driven Decisions Making (DDDM) (Making decisions based on data)				Critical Thinking	Data Culture	Data Ethics	Data Citation	Data Sharing	Evaluating Decisions Based on Data		

Figure 2. Data Literacy Competencies Matrix by [Ridsdale et al., 2015: 3] (reduced version)

The matrix is structured along five key abilities/knowledge areas (grey fields in figure 2), which are subdivided into 22 competencies. These competencies are further subdivided into conceptual competencies (blue fields), core competencies (green fields) and advanced competencies (red fields). Associated with these competencies are 64 knowledge types or tasks, which are not depicted in figure 2 but which are included in the full version of the matrix provided in [ibid.: 38]. According to the authors, the matrix is “intended to form the basis of ongoing conversations about standards for assessing and evaluating levels of data literacy, and to inform the creation of learning outcomes in data literacy education” [ibid.: 3]. The individual elements of the matrix (focusing on conceptual and core competencies) will be discussed in

<sup>3</sup> For a detailed discussion of the various literacies related to data literacy, see [Schüller, 2020: 17ff.].

<sup>4</sup> For MT literacy, a similar observation is made by [Bowker, 2019: 105].

more detail in the next section concerned with the interface between MT literacy and data literacy.

### III THE INTERFACE BETWEEN MT LITERACY AND DATA LITERACY

The *conceptual framework* of the DLCM includes the conceptual competency *introduction to data*, which is concerned with general knowledge and understanding of data and its uses and applications [Ridsdale et al., 2015: 38]. It can therefore be understood as a meta-competency permeating the other competencies of the matrix.

In the *data collection* area, the first links with the MT literacy model outlined in section 1 can be established. The core competency *data discovery and collection* (including the knowledge types/tasks data exploration, identifying and collecting useful data) is covered by point 3 of the technical MT literacy dimension (MT training, and here particularly selecting MT training data). This would include, e.g., knowledge of suitable training data repositories such as the *TAUS Data Marketplace* [http1] or the *OPUS* corpus collection [http2] or data search services such as *TAUS Matching Data* [http3]. The core competency *evaluating and ensuring quality of data and sources* (critically assessing the trustworthiness of data sources, critically evaluating data quality) is also relevant for MT training data selection. Here, the linguistic dimension of MT literacy is also relevant, particularly point 5 on linguistic quality requirements for suitable MT training data. The societal dimension also plays a role here, especially point 3 concerned with potential MT biases (which are the result of biased datasets).

The competencies listed in the *data management* area of the DLCM also interface mostly with the technical dimension of MT literacy. The core competencies *data organisation* (assessing data organization requirements, organizing data, etc.), and *data manipulation* (assessing methods for data cleaning, identifying outliers/anomalies and cleaning data) are required in MT training pipelines (selecting/compiling/organising/cleaning data). Relevant data cleaning steps prior to MT training include, e.g., filtering out sentence pairs with identical source and target sides or anomalous length ratios, filtering out empty or oversized sentences, etc. [Buj et al., 2020: 331]. The advanced competencies *data conversion*, *metadata creation/use*, *data curation/security/re-use* and *data preservation* also interface primarily with the technical dimension of MT literacy. These advanced competencies will not be discussed in any more detail here.

In the *data evaluation* area, the conceptual competency *data tools* is concerned with knowledge of data analysis tools/techniques and selecting/applying such tools/techniques. A link could be established here with data selection as part of an MT training pipeline in that selecting such data may require their automated analysis with the aim of identifying (un)desirable linguistic patterns (such as gender bias, see societal dimension) using corpus analysis tools such as *Sketch Engine* [http4]. The core competencies *basic data analysis* (analysing data, evaluating analysis results, etc.), *data interpretation* (reading data representations, identifying key take-away points and discrepancies) and *identifying problems using data* (problems in practical workplace situations and higher-level policy, environmental and other problems) could be linked to point 5 of the technical MT literacy dimension (automatic metrics for MT quality estimation/evaluation), to point 4 of the linguistic dimension (manual MT quality evaluation) as well as to points 1 (methods for estimating/measuring MTPE effort), 2 (methods for MTPE price calculation) and 3 (feasible productivity gains in MTPE) of the economic dimension. For example, analysing translation edit rate (TER), translation time or other automatic PE effort indicators and correlating these with automatic/manual MT quality indicators in a translation agency may provide a detailed picture on how the deployed MT engines are performing in terms of quality, on how translation productivity is impacted by these engines and whether there are any discrepancies between expected and actual engine quality/productivity gains. The ability to read data representations (e.g. performance indicators such as TER or BLEU scores published

by MT vendors) may also help MT buyers to select the appropriate MT system for their translation scenarios. The core competencies *data visualization* (creating meaningful graphical representations of data, etc.) and *presenting data (verbally)* (assessing the desired outcomes of data presentation, assessing audience needs, etc.) could be linked to point 4 of the economic dimension of MT literacy (setting-up/optimising business processes for MT integration), e.g. when potential MT productivity gains must be presented to the company management, which may have to sign off on the required process steps. The core competency *data-driven decision making* (prioritizing information gathered from data, converting data into actionable information, assessing/implementing possible decisions/solutions) could also be linked to this point, when data has shown that shifting to an MT-assisted translation process is indeed beneficial and the corresponding business processes have to be set-up/optimised for MT. This also touches upon point 6 of the technical MT literacy dimension, which is concerned with the technical aspects of integrating NMT systems into translation workflows/systems.

In the *data application* area, the conceptual competency *critical thinking* is concerned with the awareness of high-level issues/challenges associated with data and with critical thinking when working with data and the conceptual competency *data culture* includes recognizing the importance of data and fostering the critical use of data. The relevance of critical thinking for both MT and data literacy was already discussed briefly in section 2. For MT, [Bowker, 2019: 53] points out that “it has the potential to help if used critically, but to harm if used carelessly”. Here, a link could be established with points 2 and 3 of the economic MT literacy dimension in that a critical approach to data-driven MT will help arrive at a realistic picture of feasible productivity gains in MTPE as well as an adequate awareness of potential MT-induced business risks. Critical thinking is also relevant to the societal dimension of MT literacy, since it helps being aware of ethical aspects of MT or the phenomenon of MT bias and it helps critically reflecting MT-induced changes in the public perception/industry-internal role of human translators. The conceptual competency *data ethics* includes such an awareness of legal/ethical issues associated with data and with applying/working with data in an ethical manner.<sup>5</sup> Again, all three points of the societal dimension of data literacy are relevant here. In this context, [Moorkens, 2020: 27] highlights the responsibility of translator training institutions “to introduce business ethics and to highlight contemporary work practices in order to prepare students for future roles as both translators and translation industry workers” since they may “sooner or later become gatekeepers and makers of decisions about work practices and data harvesting that will impact many other stakeholders within the translation industry”. The core competency *data citation* (knowledge of widely accepted data citation methods and creating correct citations for secondary data sets) is less immediately relevant to MT literacy. The core competency *data sharing* (assessing methods/platforms for data sharing and sharing data legally and ethically) could be linked again to point 3 of the technical MT literacy dimension (MT training, including knowledge of suitable training data repositories). The advanced competency *evaluating decisions based on data* will not be discussed in any more detail here. It could be linked to the economic dimension of MT literacy, and here particularly to point 2 (when MT prices are adjusted in reaction to MT productivity data gathered over time) and to point 3 (when the expectations concerning MT productivity may have to be adjusted according to such historical productivity data).

#### IV CONCLUSION

This article has hopefully shown that exploring the interface between MT literacy and data literacy is a fruitful endeavour and that this interface may warrant a more extensive and detailed

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<sup>5</sup> According to [Schüller, 2020: 18], “[e]thical literacy in the context of data literacy is the ability to fully grasp the significance of data for decision making by reflecting and critically evaluating possible interpretations of these data in different contexts.”

follow-up analysis. Another promising next step in MT literacy research and education may be to establish different competency levels for individual MT subcompetencies since, depending on the particular audience and MT context, the competencies subsumed under the five MT literacy dimensions may have to be more or less well developed. For example, the Data Literacy Competence Framework by [Schüller, 2020: 25] makes a distinction between *basic*, *advanced* and *expert* levels. In translation technology research, [Abaitua, 2001: 36–37] proposes six translation technology-related roles (*consultant*, *user*, *instructor*, *evaluator*, *manager*, *developer*), which could also serve as a starting point for defining MT literacy competency levels.

Concerning the appropriate timing of data literacy education, [Ridsdale et al., 2015: 2] state that “[t]he best place to begin this initiative is the undergraduate curriculum in post-secondary institutions, due in part to their overarching goal of producing globally competitive, critically thinking, well-equipped graduates”. Against this backdrop, the *DataLit<sup>MT</sup>* project [http5] at the Institute of Translation and Multilingual Communication at TH Köln, Germany, aims to develop didactic resources for teaching data literacy to students of BA programmes in translation/LSP communication. With regard to the core subject matter of such BA programmes, the project will create didactic resources, which can be used to teach the various sub-competencies outlined in Ridsdale et al.’s Data Literacy Competencies Matrix in their translation-specific form of MT literacy. The teaching resources will be made publicly available in early 2023 in the form of Jupyter notebooks<sup>6</sup>. These resources at the interface of MT literacy and data literacy can complement the teaching resources developed in the context of more extensive MT training initiatives such as the *MultiTrainMT* project [http6]. Ideally, students working with these resources will develop an adequate MT literacy for their later professional career while at the same time becoming data-savvy citizens well equipped for the modern knowledge economy.

## References

- Abaitua, J. Is it worth learning translation technology? *International Journal of Translation*. 2001; 1(1–2): 21–39.
- Bowker, L. and Ciro, J.B. *Machine translation and global research. Towards improved machine translation literacy in the scholarly community*. Emerald Publishing (Bingley), 2019.
- Bowker, L. Machine translation literacy as a social responsibility. In *Proceedings of the Language Technologies for All (LT4All) Conference*, Paris, December 5–6, 2019: 104–107.
- Bowker, L. Machine translation use outside the language industries: a comparison of five delivery formats for machine translation literacy instruction. In *TRITON 2021: TRanslation and Interpreting Technology Online – Proceedings of the Conference*, Online conference, July 5–7, 2021a: 25–36.
- Bowker, L. Promoting linguistic diversity and inclusion: incorporating machine translation literacy into information literacy instruction for undergraduate students. *The International Journal of Information, Diversity, & Inclusion*. 2021b; 5(3): 127–151.
- Buj, D.M., Ibáñez García, D., Parcheta, Z. and Casacuberta, F. NICE: Neural integrated custom engines. In *Proceedings of the 22nd annual conference of the European Association for Machine Translation*, Lisbon, November 3–5, 2020: 329–338.
- Canfora, C. and Ottmann, A. Risks in neural machine translation. *Translation Spaces*. 2020; 9(1): 58–77.
- Cannavina, V. Machine Translation Maturity Model. *eMpTy Pages*, 2018.
- Daems, J., Vandepitte, S., Hartsuiker, R.J. and Macken, L. Identifying the machine translation error types with the greatest impact on post-editing effort. *Frontiers in Psychology*. 2017; 8: 1–15.
- Daems, J. and Macken, L. Interactive adaptive SMT versus interactive adaptive NMT: a user experience evaluation. *Machine Translation*. 2019; 33(1–2): 117–134.
- ELIS. *European Language Industry Survey*, 2021.
- European Union. The Digital Competence Framework 2.0. EU Science Hub, 2019.
- http1 <https://datamarketplace.taus.net/>
- http2 <https://opus.nlpl.eu/>
- http3 <https://md.taus.net/>
- http4 <https://www.sketchengine.eu/>

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<sup>6</sup> For a detailed discussion of the didactic potential of Jupyter notebooks in translation technology teaching, see [Krüger, 2021].



- http5 [https://www.th-koeln.de/informations-und-kommunikationswissenschaften/datalitmt--teaching-data-literacy-in-the-context-of-machine-translation-literacy\\_85011.php](https://www.th-koeln.de/informations-und-kommunikationswissenschaften/datalitmt--teaching-data-literacy-in-the-context-of-machine-translation-literacy_85011.php)
- http6 <http://www.multitrainmt.eu>
- ISO 18587. *Translation services – Post-editing of machine translation output – Requirements*. ISO Copyright Office (Geneva), 2017.
- Jiménez-Crespo, M.A. The “technological turn” in translation studies. Are we there yet? A transversal cross-disciplinary approach. *Translation Spaces*. 2020; 9(2): 314–341.
- Koehn, P. *Neural machine translation*. University Press (Cambridge), 2020.
- Koehn, P. and Wiggins, D. Everything that you need to know about customizing a great machine translation engine. *Omniscien Technologies Webinar Series*, 2021.
- Krüger, R. Technologieinduzierte Verschiebungen in der Tektonik der Translationskompetenz. *trans-kom*. 2020; 11(1): 104–137.
- Krüger, R. Augmented Translation – eine Bestandsaufnahme des rechnergestützten Fachübersetzungsprozesses. *trans-kom*. 2019; 12(1): 142–181.
- Krüger, R. Using Jupyter notebooks as didactic instruments in translation technology teaching. *The Interpreter and Translator Trainer*. 2021.
- Macken, L., Prou, D. and Tezcan, A. Quantifying the effect of machine translation in a high-quality human translation production process. *Informatics*. 2020; 7(2): 1–19.
- Maruf, S., Saleh, F. and Haffari, G. A survey on document-level neural machine translation: methods and evaluation. *ACM Computing Surveys*. 2021; 54(2): 1–36.
- Marzouk, S. and Hansen-Schirra, S. Evaluation of the impact of controlled language on neural machine translation compared to other MT architectures. *Machine Translation*. 2019; 33(1–2): 179–203.
- Misra, A. *Advancing data literacy in the post-pandemic world. A primer to catalyse policy dialogue and action*. PARIS21, 2021.
- Moorkens, J., Lewis, D., Reijers, W., Vanmassenhove, E. and Way, A. Translation resources and translator disempowerment. In *Proceedings of the 10<sup>th</sup> international conference on language resources and evaluation. ETHics in corpus collection, annotation and application workshop*, Portorož, May 23–28, 2016: 49–53.
- Moorkens, J. “A tiny cog in a large machine”. Digital Taylorism in the translation industry. *Translation Spaces*. 2020; 9(1): 12–34.
- O’Brien, S. and Ehrensberger-Dow, M. MT literacy—a cognitive view. *Translation, Cognition & Behaviour*. 2020; 3(2): 145–164.
- Ridsdale, C., Rothwell, J., Smit, M., Ali-Hassan, H., Bliemel, M., Irvine, D., Kelley, D., Matwin, S. and Wuetherick, B. *Strategies and best practices for data literacy education. Knowledge synthesis report*. Dalhousie University, 2015.
- Rivera-Trigueros, I. Machine translation systems and quality assessment: a systematic review. *Language Resources and Evaluation*, 2021.
- Sakamoto, A. Why do many translators resist post-editing? A sociological analysis using Bourdieu’s concepts. *Journal of Specialised Translation*. 2019; 31: 201–216.
- Sandrini, P. Translation 4.0 – Eine Perspektivenverschiebung. In L. Zybatow, A. Petrova, A. Stauder and M. Ustaszewski (eds.). *Übersetzen und Dolmetschen: Berufsbilder, Arbeitsfelder, Ausbildung. Ein- und Ausblicke in ein sich wandelndes Berufsfeld der Zukunft*. 2017: 139–152.
- Saunders, D. and Byrne, B. Reducing gender bias in neural machine translation as a domain adaptation problem. In *Proceedings of the 58<sup>th</sup> annual meeting of the Association for Computational Linguistics*, Online conference, July 5–10, 2020: 7724–7736.
- Saunders, D. *Domain adaptation for neural machine translation*. PhD thesis submitted at the University of Cambridge, 2021.
- Schüller, K. *Future skills: a framework for data literacy*. Hochschulforum Digitalisierung, 2020.
- Specia, L., Raj, D. and Turchi, M. Machine translation evaluation versus quality estimation. *Machine Translation*. 2010; 24(1): 39–50.
- Sulubacak, U., Caglayan, O., Grönroos, S.-A., Rouhe, A., Elliott, D., Specia, L. and Tiedemann, J. Multimodal machine translation through visuals and speech. *Machine Translation*. 2020; 34(2–3): 97–147.
- TAUS. *Pricing machine translation post-editing guidelines*. TAUS, 2013.
- Toral, A. Post-editeese: an exacerbated translationese. In *Proceedings of Machine Translation Summit XVII: Research Track*, Dublin, August 19–23, 2019: 273–281.
- Way, A. Quality expectations of machine translation. In J. Moorkens, S. Castilho, F. Gaspari and S. Doherty (eds.). *Translation Quality Assessment: From Principles to Practice*. Springer (Cham), 2018: 159–178.