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What motor vehicles and translation machines have in common - a first step towards a translation automation taxonomy

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ABSTRACT

In society in general and in professional translation in particular, translation is increasingly automated. However, in Translation Studies, we lack an updated and future-proof taxonomy of translation automation to understand the evolving and dynamic relationship between humans and digital technologies and to identify different levels of translation automation. In the field of driving automation, the Society of Automotive Engineers has established an influential and widely applied taxonomy of six levels of automation, ranging from no automation to fully automated driverless cars. Taking a first step towards providing a taxonomy of translation automation, the paper proposes and discusses a similar taxonomy of six levels of translation automation.

Keywords: taxonomy, translation automation, translation systems, machine translation, translation theory

1. Introduction

Automation of processes is taking place in many service sectors. According to the Cambridge Dictionary (2020), on a general level, automation means either “the use of machines and computers that can operate without needing human control” or “the use of machines or computers instead of people to do a job”. In the automotive industry, the control of motor vehicles is systematically transferred from humans to machines in order to achieve driverless cars that can safely transport humans from one destination to another under all conditions.

In the translation industry, the control of the translation process is being transferred from translators to computers to an increasing extent (European Language Industry Survey 2020). The ultimate aim appears to be the development of digital technologies that can translate all types of texts from one language to another obtaining a quality equal to human translation. However, it is often questioned whether a computer will ever be able to deliver human-quality translations. In the words of O’Hagan (2019: 2), “the human-machine relationship is in a state of flux, with uncharted paths ahead”. Nonetheless, we think that it is safe to assume that the relationship between translators and machines will become ever closer in the future, and we argue that we need to investigate the degree of symbiosis between technology and human translation (cf. Alonso and Calvo 2015: 136). To this end, we need an updated and future-proof taxonomy of translation automation (TA) to understand the deepening and dynamic relationship between humans and digital technologies and to identify different levels of TA.

In driving automation (DA), the decreasing degree of human control over cars is described using a taxonomy outlined by the Society of Automotive Engineers (SAE) (SAE 2018). The taxonomy divides DA into six levels ranging from no automation (level 0) to full automation (level 5), the latter being generally known as driverless cars. We argue that DA and TA technologies and the ways that humans interact with these technologies share many characteristics. For instance, the goal of DA is that a vehicle can handle the entire travel pathway from a point of origin to a specified destination, taking into account objects and events in the driving environment. Similarly, the goal of TA is that a translation system can handle the process of going from a source text (ST) (point of origin) to a target text (TT) (destination), establishing the necessary semantic relationships between the texts. Also, both DA and TA employ artificial intelligence (AI) to reach these goals, and the levels of automation are typically distinguished based on the role of the user of the technology, i.e. the person who is in the “driver’s seat” (Schatsky and Schwartz 2015: 13; in Krüger 2019a: 144). Within Translation Studies (TS) this would be the translator.

Inspired by the parallels between DA and TA, this paper discusses whether it is possible to use the SAE taxonomy as a useful framework for describing different levels of TA and takes a first step towards developing a TA taxonomy. Hence, this paper aims at providing a framework for understanding the relationship between translators and digital technologies. In so doing, it is our hope that the paper may contribute to the theoretical rethinking of the discipline of translation as called for by Alonso Jiménez and de la Cova (2016: 14) emphasising that the discipline currently finds itself at a paradigmatic juncture.

Applying the guiding principles and concepts of the SAE taxonomy, we hope to suggest a TA taxonomy that may be useful and understandable across disciplines, including software development, media and TS, as well as in the translation industry and in public discourse, especially since the SAE taxonomy is already widely applied. In other words, the proposed taxonomy will hopefully make it easier for people to understand TA, not only within TS, but in society as a whole, which would address the “casual user’s” lack of MT literacy reflected on by e.g. O’Brien and Ehrensberger-Dow (2020). In line with this, Pym highlights that teaching society about what MT can and cannot do is an important task for translation researchers: virtually everyone is using MT, “so they might as well know something about it” (Pym 2019: 7). Typically, MT and TA (sometimes also referred to as automatic translation) are used as synonyms (Bundgaard 2017: 10), even though MT is just one type of digital technology covered by TA. Also, several

TS researchers have already dealt with TA, but, to our knowledge, no one has provided an operational definition of the concept. However, in a general manner, Tieber describes TA as the digital outsourcing of translation processes (Tieber 2019: 241), and he draws on Rozmyslowicz (2014) who describes TA as a fully automated and agentless-decoding process (Tieber 2019: 245).

We expect that in the future different forms of interplay between humans and machines will be adopted to accommodate different needs. We also anticipate a range of new translation tools and/or features that could be placed on a continuum ranging from technologies that aim at assisting the translator at one end to technologies aimed at automating the translation process to the greatest possible extent at the other. In this paper, we will not speculate on what is the best place for machines and humans in translation. Nor will we evaluate technologies' usability (for a discussion of usability, see Krüger 2019b) or measure whether certain tools generate output of acceptable quality. We simply take as our starting point the fact that, in the language industry, humans and machines are highly interdependent and that they are (probably) going to be even more so in the future, not least because it is generally believed that automation goes hand in hand with higher profits.

In Section 2, we briefly outline the development of translation technologies and broadly review what has been said about translators' interaction with computers in TS. Further, we reflect on existing spectrums contrasting human translation and automatic translation. In Section 3, we present the concept of DA and discuss the SAE taxonomy (2018). In section 4, we present a first attempt at a TA taxonomy based on the DA taxonomy and discuss how DA concepts might be adapted to the field of translation. Section 5 finishes with some concluding remarks and recommendations regarding where to go from here.

2. Humans and machines in translation – who is translating?

In the 1950s, MT research explicitly linked humans and machines for the first time. Back then, the ultimate purpose of MT was to provide fully automatic high-quality translations, and the role of humans (if any) was to pre-edit STs and/or to edit MT output by means of post-editing (PE), which means that MT output is generated first and then edited in another step. Humans carrying out PE were referred to as MT's human partners. Hence, at this stage, MT was mainly considered a computer-oriented activity (Vieira 2019: 319).

The 1966 Automatic Language Processing Advisory Committee report (ALPAC 1966) put an end to MT development when it concluded that MT would not be able to produce translations of acceptable quality and suggested that research should instead focus on machines assisting translators (O'Hagan 2019: 3). In the 1980s, Kay (1980) theorized an electronic machine-aided tool called "The Translator's Amanuensis". This tool would allow the machine to carry out routine tasks in translation. Shortly after, Melby (1981) envisioned a tool that he called "The translator's workstation" integrating different levels of machine aids. In both visions, translators were in control of the translation workflow and could decide which tools to use and how. These tools resemble what we now know as computer-assisted translation (CAT) tools, which typically include translation memory (TM) systems, termbases, MT and nowadays sometimes also automated content enrichment (ACE) (DePalma 2017: 2; Krüger 2019a: 163; O'Hagan 2019: 2).

The basic idea of TM is to reuse translations produced by humans by storing them in a database as segmented and paired source and target texts to be retrieved by translators translating identical or similar segments (see, for instance, Christensen and Schjoldager 2010: 89). The translator (or the language service provider) can decide to have the ST either pre-translated using TM and/or MT or translate segment by segment in a so-called interactive mode, in which translators interact with the CAT tool while the final version of the TT is being generated. A termbase is basically a multilingual database containing approved terminology and related information helping translators produce a terminologically consistent TT. As for MT, the basic idea is to translate texts from one natural language into another using computers without any human involvement. In the 1980s, MT systems typically adopted a rule-based approach, while the approach in the 1990s was mainly statistical drawing on multilingual corpora. From around 2016, these approaches were displaced by neural MT (NMT) or hybrid systems. NMT is based on so-called artificial neural networks aiming to reproduce the learning processes of the human brain. NMT systems are trained using all sorts of material, including TM databases, termbases, and multilingual and monolingual corpora. The technology makes use of algorithms based on linguistic patterns to locate candidate translations from previous human translations (Tieber 2019: 244). With an ACE tool, relevant concepts in the ST are automatically identified and linked to external resources that may assist the translator in finding additional information (DePalma 2017: 2; Krüger 2019a: 163; O'Hagan 2019: 2).

We would like to stress that there seems to be some terminological confusion in the literature regarding some central concepts of CAT and MT. For instance, CAT was earlier distinguished from MT because it

aimed at assisting translators, whereas MT aimed at replacing translators or only required human involvement in pre- and post-editing processes (O'Hagan 2019: 3). Today, however, as TM and MT tend to be integrated into a CAT tool, a distinction between MT and CAT is no longer possible, making it hard to say if machines are assisting humans or vice versa (Bundgaard 2017: 15). Similarly, Vieira (2019: 320) states that the boundaries between TM and MT have become blurred. For example, in MT-assisted TM, translators are presented with TM proposals produced by humans as well as output generated by a machine, and they must edit these in order for the translation to be included in the TM databases. Also, the fact that MT engines are typically trained using in-house human-produced TM databases and termbases makes the distinction between TM and MT even harder. The term CAT also seems problematic, as it is often used as a synonym for TM tools, even though TM is actually a subcategory of CAT (Zetzsche 2019). The terminological confusion also applies to the term MT, which is used to refer to the automatic translation of a text with no human involvement as well as to automatic translation combined with pre- and/or post-editing by humans. Moreover, MT is used as an umbrella term covering a wide range of paradigms such as rule-based MT, example-based MT, open source or generic MT, pragmatic-based MT, statistical MT, and NMT, albeit these systems adopt very different technological approaches to render the content of texts from one language into another. Naturally, for a TA taxonomy to be useful and future-proof, its terminological and conceptual framework must be consistent.

According to Krüger (2019a: 142), the speed with which new technologies¹ are implemented in the translation industry makes it hard even for highly professional translators and translation scholars to keep up with the ongoing development, and García (2015: 85) argues that TA is bound to be a key factor in the language industry in the coming years. Along the same lines, Alonso and Vieira (2017: 348) state that we can expect MT to become increasingly ubiquitous because more and more platforms and devices will surely integrate TA. Hence, TA will not only play a vital role in the language industry, but in society as a whole (Alonso and Vieira 2017: 353). Thus, for instance, many are currently using free online MT engines like Google Translate or DeepL to help them understand and produce texts in foreign languages (Tieber 2019: 242). As a result, from being an activity carried out mainly by professional translators, translation has now become a very basic and widespread human activity (Pym 2019: 1).

¹ For an updated overview of translation technologies, see Garcia (2015) and Krüger (2019a).

2.1 Translation automation spectrums

We will now review the only two existing spectrums illustrating the relationship between humans and digital technologies that we were able to find: the spectrum of Hutchins and Somers (1992) contrasting human involvement and mechanization (automation) in the translation process and Vieira's (2019) spectrum of human agency in the PE process.

Hutchins and Somers' (1992: 148) spectrum (Figure 1) operates with four different translation modes or levels of automation: *Human translation* (HT), *Machine-aided human translation* (MAHT), *Human-aided machine translation* (HAMT), and *Fully automated high-quality translation* (FAHQT). HT is a human translation mode involving no technological aids, i.e. a mode in which a translator controls and is ultimately responsible for the translation process as a whole. In MAHT, a translator is in charge of the translation process, but is provided with different kinds of linguistic support as in the first generations of TM systems. In HAMT, MT systems essentially establish relationships between the ST and the TT, while humans assist the process when needed, e.g. in the form of pre- or post-editing. Hutchins and Somers use the term CAT to cover both MAHT and HAMT. In FAHQT, the machine carries out translation without human intervention obtaining a translation quality equal to human translation quality, meaning that it replaces the translator. Consequently, this is a case of full TA.

Figure 1: Hutchins and Somers' spectrum of translation methods as illustrated by Bundgaard (2017: 9)

Hutchins and Somers' spectrum has lately been criticized for being outdated (e.g. Christensen et al. 2017) because it does not reflect the way in which existing tools are incorporated into each other (Bundgaard 2017: 8; O'Hagan 2019: 2-3, and Vieira 2019: 320). Moreover, Krüger notes that "due to the continuous development of new technologies, the translation industry is moving ever closer to the *mechanization* endpoint of Hutchins and Somers' (1992) well-known TA continuum" (Krüger 2019b: 93; original emphasis), hinting at the need for a more fine-grained continuum, in particular towards the left end of the continuum.

Vieira's (2019) spectrum of agency (Figure 2) addresses PE as a multifaceted CAT activity. Interestingly, he argues that the concept of PE is in a state of terminological flux as PE can currently be seen to comprise different tasks and procedures due to an integration of various technologies into CAT. Vieira argues that a key factor in understanding the diverse nature of PE is to describe PE according to the extent that translators are expected to exercise agency in the PE process. Vieira therefore seems to

agree with us that it might be fruitful to operate with different levels of symbiosis between humans and machines.

Figure 2: Spectrum of agency in the post-editing process (Vieira 2019: 327)

Vieira's spectrum operates with three levels of PE automation: automatic PE, static PE and PE with interactive/adaptive MT suggestions. In automatic PE, MT features are used to improve the MT output after it has been generated. Thus, there is no human involvement, and it is therefore referred to as MT-centred. PE with interactive/adaptive MT suggestions, referred to as human-centred, is a mode in which the translator interacts with the system while the TT is being generated. The translator naturally has more control in this mode. Here, MT may be used to predict and complete human translations as they are being typed, and the MT system can react to and learn from human edits on the fly, i.e. in a reciprocal interactive manner. Consequently, interactive and adaptive MT reflects the characteristics of so-called "augmented translation" (DePalma 2017; Lommel 2018; Krüger 2019a), in which the translator is at the centre, but can decide to use an advanced suite of technologies, most typically CAT tools. In static PE, MT output is generated first and then edited in a separate step, and is positioned in the middle of the spectrum. It can move closer towards either end of the spectrum, depending on how MT is used and on translators' level of freedom in deciding how to draw on MT suggestions. Comparing the two spectrums, we observe that Vieira's spectrum does not include a mode without technology or even without MT, and that automatic PE might correspond to FAHQT in that of Hutchins and Somers. Furthermore, static PE and PE with interactive/adaptive MT in Vieira's spectrum appear to correspond to either HAMT or MAHT in that of Hutchins and Somers, depending on the level of agency. Worth noting is also that Vieira's spectrum does not address TA as such, but merely PEMT. Also, it does not appear to have an interdisciplinary scope since it seems to be primarily intended for a reader versed in PE.

Using the two spectrums to reflect on the development of translation tools, we found that, at first, the use of translation tools was aimed at replacing translators to the largest possible extent (FAHQT) by means of machine-centred technologies. Then, the focus changed to more human-centred technologies by means of MAHT and HAMT or combinations thereof. It seems, however, that we are now standing at a crossroads. Either we are going to witness a development towards more human-centred approaches like augmented translation, in which humans and machines will find a "harmonic-co-existence" (Alonso

and Vieira 2017: 353), or towards a machine-oriented approach in the form of AI-controlled TA, gradually making CAT tools redundant (García 2015: 85; Zetzsche 2019: 179).

3. Driving automation and the SAE taxonomy

In this section, we briefly explain the concepts of the SAE taxonomy (SAE 2018: 2-18) that we consider relevant to the proposed TA taxonomy. The interplay between humans and machines in DA and the six levels of DA are depicted in Figure 3 below.

Figure 3: Hussain et al.'s (2018: 28) simplified version of the SAE taxonomy (2018)

SAE defines DA as the performance of hardware/software systems of part or all of the **Dynamic Driving Task** (DDT) on a sustained basis. DDT is defined as all real-time operational and tactical functions required to operate a vehicle in on-road traffic, excluding strategic functions such as trip scheduling and selection of destination. Tactical efforts include vehicle manoeuvring in traffic during a trip, e.g. deciding to change lanes, while operational efforts involve “split-second reactions that can be considered pre-cognitive or innate, such as making micro-corrections to steering, braking and accelerating” (SAE 2018: 34). The DDT covers the basic activities necessary for the sustained operation of a vehicle motion. It comprises **lateral** vehicle motion control, which basically means vehicle steering, and **longitudinal** vehicle motion control, which refers to acceleration and deceleration. Furthermore, the DDT covers **Object and Event Detection and Response** (OEDR), which basically refers to keeping an eye on the road and the surroundings and reacting when necessary. In SAE terms, OEDR covers a) monitoring the driving environment, which refers to detecting, recognizing and classifying objects and events and preparing to respond as needed, and b) executing an appropriate response to such objects and events as needed to complete the DDT and/or a DDT Fallback. **DDT Fallback** is the response by the user or an automated driving system to a) perform the DDT (i.e. take over driving) or b) achieve a minimal risk condition (e.g. bringing the vehicle to a stop). This becomes necessary after the occurrence of one or more DDT performance-relevant system failures (malfunction in the DA system) or upon exiting an **Operational Design Domain** (ODD). The ODD refers to the operating conditions under which a given DA system, or a feature thereof, is designed to function. This includes environmental, geographical, and time-of-day restrictions and/or the required presence or absence of certain traffic or roadway characteristics. An example of an ODD could be that a vehicle can operate only within a geographically limited area, only during daylight and only at speeds below 25 mph.

Vehicle control is considered **sustained** when a driver or a DA system performs part or all of the DDT both between and across external events (such as other vehicles, lane markings and traffic signs), including responding to these events. Features such as automated emergency braking, which only provide momentary intervention, do not perform any part of the DDT on a sustained basis. A **DA system** consists of hardware and software that are collectively capable of achieving DA levels 1-5. In contrast, an **Automated Driving System (ADS)** refers to hardware and software performing the entire DDT only at levels 3, 4 and 5. The level of DA depends on which **DA features** (functionalities) are engaged at a given point in time. For instance, although a vehicle is equipped with a DA system that can perform at different levels, the level of DA is always determined by the DA features which the human driver decides to engage or disengage during a trip.

In the taxonomy, DA systems are categorized into six mutually exclusive levels (0-5), based on whether the DA system:

1. performs the longitudinal or the lateral vehicle motion control subtask of the DDT – or both simultaneously.
2. also performs OEDR.
3. also performs DDT Fallback.
4. is limited by an ODD.

At level 0, a human driver operates the vehicle without automation features. Today, this is the case for most cars on the roads. This means that the driver must have feet on the pedal(s), hands on the wheel and eyes on the road to control the vehicle performance. In case of a system failure or external events, the driver must respond appropriately. **At level 1**, the driver controls the vehicle, but features either take over steering (e.g. in the form of a lane centering feature) or acceleration/deceleration (e.g. in the form of an adaptive cruise control feature). This means that the driver must have feet on the pedals or hands on the wheel, and must still monitor the road and the vehicle performance at all times. **At level 2**, the DA system takes over both steering and acceleration/deceleration, but the human driver monitors the driving environment and executes appropriate responses to objects and events. **At level 3**, the driver no longer needs to supervise the performance of the vehicle or the road and traffic conditions, but still has to take control when requested to do so by the system. An example of a level-3 feature is the traffic jam chauffeur that can follow the preceding car in stop and go traffic jams and can perform

automated lane changing, though only on highways or highway-like roads. **At level 4**, the system performs the entire driving task within a limited ODD, and the driver will not be required to take control, meaning that a level-4 system operates the vehicle completely, but only under certain conditions (e.g. a closed campus shuttle feature or a local driverless taxi). **At level 5**, the features can drive the vehicle everywhere and under all conditions, regardless of weather, time of day and geographical restrictions. Hence, level-5 vehicles are driverless cars.

4. Towards a translation automation taxonomy

In this section, we take a first step towards a taxonomy of TA. While aiming to follow the SAE taxonomy (2018) as much as possible regarding form and categorizing concepts, we will not pretend that the proposed taxonomy is tenable and consistent down to the last detail. We merely hope to encourage a discussion of TA and invite constructive criticism of the taxonomy.

Like the SAE taxonomy, our first version of a TA taxonomy operates with six levels, ranging from no TA to full TA. Briefly explained, the level of TA depends on whether a translator or a system is responsible for ST analysis and/or TT production as well as the detection and correction of errors and inadequacies, referred to as the Dynamic Translation Task (DTT), whether the translator or the system is responsible for responding to system failures (DTT Fallback), and whether the system can operate under all conditions, referred to as the Operational Design Domain (ODD). Figure 4 provides an overview of the SAE concepts in comparison with the proposed TA concepts. Below, we will discuss in more detail the operationalisation of the different concepts.

Figure 4: Driving automation and translation automation terminology

In Figure 5, we present our proposal for a TA taxonomy. In order for the taxonomy to be understandable, we first discuss the conceptual framework, and then we describe the six TA levels and reflect on how current translation technologies fit into the taxonomy.

Figure 5: Levels of translation automation

4.1 Conceptual framework

When adapting the SAE taxonomy, we faced a number of challenges. It was particularly difficult to define which subtasks constitute the **DTT**. In DA, the DDT is defined as all real-time operational and

tactical functions needed to operate a vehicle in on-road traffic, excluding strategic functions such as trip scheduling and destination selection. Tactical efforts include vehicle manoeuvring in traffic during a trip, while operational efforts involve pre-cognitive or innate efforts (SAE 2018: 34). Adjusted to translation, the DTT could be defined as all real-time operational and tactical functions involved in the translation process, excluding strategic functions. Examples of strategic functions would be choosing a macro-strategy, configuration of the translation system, including choosing an MT engine and/or a TM database and selecting a target language (cf. Krüger 2019a). From the definition outlined in the SAE taxonomy, it seems that tactical and operational efforts cover conscious and unconscious decision-making processes, respectively. This is also a distinction commonly made in Translation Process Research (Göpferich 2008; Prassl 2010). However, when defining the DTT, the central challenge is that the taxonomy ranges from no TA to full TA implying that we need to compare cognition in human translation (Krings 1986), cognition in augmented translation in which cognition is distributed between the human and the machine (O'Brien 2017), and translation by means of artificial neural networks as in NMT, which aims at mimicking the human brain. In other words, we need to understand the cognitive components, i.e. how semantic relations are created between a ST and a TT, at the different TA levels. However, this would result in an extensive discussion which would exceed the scope of this paper.

Arguing that the DTT covers all non-strategic functions, we see DTT as encompassing the part of the translation process that Krüger (2019a: 148) refers to as the translational “Kerntätigkeit” or the “inner” translation process, and Chesterman (2013:156) as “the translation act”. The proposed taxonomy therefore excludes phases such as the pre-translation phase (for instance, project initiation and preparation) and the post-translation phase (for instance, project handling and post-processing), referred to by Krüger (2019a) as the “outer” translation process, and by Chesterman (2013) as the “translation event”.

In DA, the DDT covers subtasks such as (1) motion control, including steering using hands and acceleration/deceleration using feet, and (2) monitoring the driving environment and responding appropriately. In TA, the DTT subtasks appear to cover the activities typically carried out during a translation act, and these may potentially be carried out solely by the translator (level 0), by the translator and the system in combination (levels 1 and 2) or entirely by the system (levels 3-5). In the following, trying to identify the subtasks of the DTT, we primarily take our point of departure in Krüger's (2018) understanding of translator competences, though his focus is on CAT processes, not on human or fully automated translation processes.

According to Krüger, the inner translation process includes all work phases related to ST reception and TT production. As stated by Krüger, the implementation of translation technology in translation processes has changed the competences needed by translators. As the importance of text production skills has decreased, the translator must develop text adaptation and text optimization skills, including recombination and re-contextualization skills. According to Krüger, the importance of text reception skills, including text evaluation and text selection skills, will increase, as translators will typically work with segment-level translation proposals retrieved by the system. He argues that text reception includes what, in CAT, is typically referred to as ST reading and evaluation and the reading and evaluation of target language translation data, e.g. translation proposals (cf. Krüger 2018: 121-122). However, as “reception” implies a level of meaning-making that does not seem to be present in processes without human intervention, “reception” seems too narrow for our purposes. O’Brien (2017) argues that in PEMT, the post-editor has to carry out two types of ST analysis: of the original ST sentence and the corresponding MT proposal. In our taxonomy, we propose to name this subtask **control of source text analysis**. Since the term “text production” is generally used to refer to the subtask of transferring the ST content to the TT (Krüger 2018; O’Brien 2017), either in the form of translating from scratch or adapting and optimizing translation proposals, including recombination and re-contextualization, we name this subtask **control of target text production**. Within (N)MT, control of ST analysis might correspond to the encoding of ST sentences (Forcada 2017; Hassan et al. 2018: 3), and control of TT production might correspond to the decoding of TT sentences (ibid).

While a DA system can take over steering *or* acceleration/deceleration, it would seem questionable for a TA system to take over analysis of the ST without also taking over the production of the TT, and vice versa. Thus, as control of ST analysis and control of TT production seem to be more inextricably linked with each other in TA than is the case with steering and acceleration/deceleration in DA, it might therefore be more sensible to distinguish between whether the translation system or the translator performs both ST analysis and TT production. Obviously, this is a central question that must be addressed in order to reach a widely applicable and acceptable taxonomy within the field of TA.

When driving a conventional vehicle, the driver needs to keep an eye on other vehicles, traffic signs, pedestrians etc. Similarly, in a translation process, translators essentially need to monitor the translation task and respond to elements such as translation errors and other inadequacies. In our TA taxonomy, this subtask is covered by the concept of **error and inadequacy detection and response**. In our interpretation, this refers to the monitoring of the translation process during the DTT and the response

to detected errors and inadequacies, e.g. the correction of syntactical errors and terminological inconsistencies, as well as taking into account the co- and context of the TT and other influences such as the translation brief, style guides, norms, term bases etc.

In DA, **Fallback** refers to the response by the driver or the system to system failures. If, for instance, a camera that is supposed to detect lane markings is not working, the system will prompt the driver to take over driving or at least to achieve a minimal risk condition, i.e. reduce the risk of a crash when a trip cannot or should not be completed. The system will also request the driver to take over if the vehicle exits the ODD. In TA, we would say that **DTT Fallback** occurs when the TA system experiences a system failure such as software and hardware problems, when ODD limits are about to be exceeded, and the translator or the system needs to take action. System failures might occur when, for instance, a concordance feature or an MT engine stops functioning. In DA, an ODD refers to the operating conditions under which a DA system is designed to function. Thus, for instance, an ADS feature can be designed to operate only in low speed traffic and under fair weather conditions or within a geographically limited area such as a parking lot. In TA, we imagine that the **ODD** might be limited to certain language combinations, text genres and quality levels, for instance. Examples are the Canadian MT system METEO, which was specifically designed for the translation of weather forecasts, and MT systems that are developed for specific language combinations. While most translators can easily imagine TA system failures – witness the many discussions of CAT errors on professional translation forums like Proz.com – it is more difficult to imagine that a TA system is activated for a specific language combination, for instance, and that this language combination would change during translation. The concept of ODD in TA therefore needs to be discussed further and developed.

As can be seen from Figure 5, parallel to the SAE taxonomy, we suggest defining the TA levels by reference to the roles played by the user and the system during the automated process. When referring to hardware and software that are collectively capable of levels 1-5 TA on a sustained basis and specifically designed to function within an ODD, we speak of a **TA system**. When referring to hardware and software that can perform the entire DTT at levels 3, 4 and 5, we speak of an **Automated Translation System (ATS)**. We understand both TA systems and ATS to be systems that are designed to work with at least one ST (point of origin) and a TT (destination) to establish semantic relationships between texts on a segment or a text level (see Alcina 2008). O'Hagan (2019: 2) refers to tools that can establish such relationships as translation-specific technologies, mentioning MT as an example. Along the same lines, Krüger (2018: 120-121) refers to TM and MT as digital translational data with a “short

distance” between STs and TTs. As for the concept of user, the taxonomy operates with a **translator**² and a **DTT Fallback-ready user**. Depending on the level of TA, the translator is responsible for part of or all of the DTT, and at level 3, the translator is described as a DTT Fallback-ready user in the sense that while the TA system is handling the DTT, the translator needs to be receptive, i.e. ready to focus her or his attention on system failures and perform the DTT Fallback on request by the system.

As already mentioned, the level of TA is determined by the TA features that are engaged at any given instance of operation of a TA system. Inspired by the SAE taxonomy, we regard TA features as functionalities that are engaged at a given level of TA within a particular ODD. Each TA system may have multiple features associated with a particular level of TA and ODD, each fulfilling a specific purpose. Inspired by SAE (2018: 2), features that do not change or eliminate the role of the translator in performing part of or all of the DTT may be excluded from the scope of TA.

It should now be clear that it no longer makes sense to conceptualize TA by means of modes such as MAHT and HAMT as in the spectrum by Hutchins and Somers. Instead, we suggest to distinguish TA levels depending on the features that are engaged. Thus, for instance, as a CAT tool can include several features such as a termbase, a TM database, a concordance feature and an MT engine, each providing functionalities that automate part of or all of the DTT, the level of TA depends on which of these are engaged. As the level of TA is determined by the features engaged, a CAT tool can be said to be a TA system that includes features supporting different levels of TA. Thus, for instance, a CAT tool equipped with MT only operates at a certain TA level as long as this feature is turned on: if, at some point during the DTT, the translator decides to deactivate the MT feature and translate ST segments her- or himself, this would decrease the level of automation.

4.2 Levels of translation automation

Based on our operationalization of the categorizing concepts in the taxonomy, we now describe the six TA levels in more detail and discuss how some existing TA features might be described from this perspective.

At level 0 (No TA), it is the translator who at all times performs the entire DTT. Hence, the translator controls ST analysis and TT production, meaning that the translator establishes the semantic

² SAE (2018) distinguishes between several types of “human users”, such as conventional and remote drivers, passengers and driverless operation dispatchers. Since this distinction is not used in the SAE taxonomy, we will not attempt to adapt it to TA at this point. However, it may become relevant at a later stage.

relationships between the ST and the TT. At the same time, the translator monitors the translation task and responds to translation errors and inadequacies, thereby taking into account the co- and context and relevant controlling influences such as style guides and the translation brief. The translator might also use external aids such as online dictionaries (IATE, for instance), but since this does not change or eliminate the role of the translator, we do not regard such aids as TA features. When system failures occur, it is the translator who is supposed to take action by means of DTT Fallback. Since translators, at least in theory, are able to translate texts within all domains and all language combinations, ODD is considered irrelevant at level 0.

At level 1 (Translator Assistance), the TA system takes over either control of ST analysis or control of TT production within a limited ODD. In other words, the translator must either evaluate the ST or produce the TT while monitoring the translation task in terms of detecting and responding to errors and inadequacies. We assume that a conventional concordance feature, when activated, might be an example of a level-1 TA. The argument would be that this feature searches for words or chunks of words within a TM database, which might resemble ST analysis. However, it is the translator who must select which words or chunks of text retrieved from the TM are to be reused in the TT (if any), and this might resemble text production. Further, the translator must take action if system failures occur. Another example of level-1 TA might be a TM database that retrieves TM proposals (if any), but it is the translator who evaluates these and produces the TT segment either by accepting or editing the proposed match or translating the segment from scratch. Another example might be active terminology detection integrated into CAT tools, a functionality that pushes terminology to the translator at the moment it is needed if a sentence to be translated includes a term contained in the termbase.

At level 2 (Partial TA), the system performs ST analysis and TT production within a limited domain, while the translator monitors the translation task in terms of detecting and responding to errors and inadequacies. Further, the translator is responsible for taking action in case of system failures. An example of level-2 TA might be when an MT system produces a TT within a specific language combination or is limited to a certain quality level, which the translator then has to evaluate and correct. Drawing on Vieira's conceptualisation (2019), we assume that this can take place in the form of static PE when the translator edits MT output in a separate step or in the form of PE with interactive/adaptive MT suggestions while the system produces the TT using human input "live". The translator's task of responding to errors and inadequacies in the output might take the form of either "full" or "light" PE, a distinction commonly made in TS literature (e.g. Vieira 2019).

At level 3 (Conditional TA), an ATS performs the entire DTT within a limited ODD on a sustained basis, while, at all times, the translator must be ready to take over the translation task, i.e. handle DTT Fallback. Hence, she or he must be receptive to system failures and ready to take over, but only when prompted by the ATS to do so. An example might be a feature that is able to perform automatic PE, i.e. an MT system that translates and afterwards improves the output, but only within a limited domain and obtaining a certain quality level, and the translator must be ready to take control over the process when requested by the system to do so.

At level 4 (High TA), an ATS performs the entire DTT and DTT Fallback within a limited ODD. Hence, the system controls ST analysis and TT production, identifies and corrects errors and inadequacies as well as responds to system failures. This means that the ATS can operate without human intervention, but only within its ODD. An example could be an MT system able to produce a TT at the expected quality level within a specific language combination and within a specific genre.

At level 5 (Full TA), the performance by an ATS of the entire DTT and DTT Fallback is sustained and unconditional. Hence, the ATS can operate under the same conditions as a human translator. This would be a situation when an MT system produces satisfactory TTs in all contexts without human intervention.

To sum up, at levels 0-2, the translator is in the translator's seat and is translating (even if parts of the DTT are handed over to a TA system in levels 1 and 2): the translator monitors the translation task at all times, corrects any errors and inadequacies and takes over in case of system failures. At levels 1-2, features could be referred to as support features. At levels 3-5, the translator hands over the entire DTT to an ATS, meaning that translation is performed by the system. At these levels, features engaged could be referred to as automated translation features. Hence, levels 1-2 basically involve human-centred features, whereas levels 3-5 involve machine-centred features. In this sense, our taxonomy will be applicable regardless of whether augmented translation or a machine-oriented approach will prevail in the future.

5. Discussion and conclusion

Based on the assumption that DA and TA have a lot in common, this paper proposes to use the SAE taxonomy of DA as a basis for a TA taxonomy and takes a first step towards this by providing descriptions of six TA levels. The suggested taxonomy basically describes whether it is the translator and/or the system that translates a text by means of ST analysis and TT production and checks for and

corrects errors and inadequacies, whether the translator or the system responds to system failures, and whether or not the performance of the system is limited to a certain domain.

Our aim was to provide a framework for understanding the concept of TA and to gain knowledge about the interplay of translators and digital technologies in the digitalized age characterized by automation in most sectors in society. Several TS researchers have dealt with TA, but, to our knowledge, no one has provided an operational definition of the concept. Applying the categorizing concepts discussed in this paper, we define TA as the performance by hardware and software systems of part or all of the operational and tactical DTT on a sustained basis during the translation task.

Our TA taxonomy classifies TA into six levels, and the level exhibited in any given instance is determined by the roles played by the translator and the TA system as well as the feature(s) engaged. Adopting the idea of features as a defining principle for the six levels of TA hopefully allows for a TA taxonomy that is open and flexible enough to contain future TA developments in years to come because it reflects the fact that the interplay between translators and machines is constantly evolving. Worth noting is that TS literature on translation technology has already begun to use the term feature when referring to specific functionalities integrated into translation tools (e.g. Alonso and Vieira 2017; Vieira 2019: 320). Thus, for instance, Zetsche (2019: 179) emphasizes that “there will be many more features aiming at AI-controlled automation in workflow management, quality control and machine translation that translators will have to integrate into their working arsenals.”

We hope that the proposed taxonomy may have theoretical and empirical consequences for future research. However, in order to be able to add value to the field of TS and other relevant areas, the taxonomy needs to be discussed and tested. We therefore welcome feedback from scholars, system developers, networks and organisations that explore human interaction with translation technology³. Further, we need to know whether the intended audience finds the taxonomy useful, and whether it can contribute to the dialogue between disciplines concerned with TA. At a more specific level, we also welcome discussions of our operationalization of the categorizing concepts of the taxonomy, as it turned out to be a very intriguing and complex endeavor to adapt DA concepts to the field of translation. In this respect, in order to define the DTT in more detail, process studies are needed to investigate how

³ Examples of such networks and organisations are the Translation Automation User Society (<https://www.taus.net>) and the HAL (Humans, Applications and Languages) research network (<https://halnetwork.wixsite.com/halnetwork>).

humans and machines as well as humans and machines in combination generate translations. In particular, we need to learn more about what characterizes tactical and operational functions at the different TA levels (cf. Section 4.1). Also, we need to explore how the features currently used by translators fit into the taxonomy.

We want to stress that by proposing a TA taxonomy we do not mean to say that the field of professional translation should necessarily aim at developing translatorless translation systems, but we want to emphasise that society at large and the translation industry in particular are already witnessing steadily increasing levels of TA. TA can be considered an example of the automation of “knowledge work”, i.e. cognitive and intellectual tasks, as described by Davenport and Kirby (2015). According to Alonso and Calvo (2015: 149), there are both optimistic and pessimistic interpretations of the increasing automation of translation processes. Pessimists tend to assume that translation technologies are bound to take over translators’ jobs, leading to a dehumanization of translation, while optimists seem to expect that an increasing use of technology might lead to new, less mechanical and more dynamic human roles and thus to new and rehumanized processes (Pym 2019). Pessimistically or just realistically, Wei (2018; cited in Pym 2019) assumes that at some point most of the work now done by professional translators will be replaced by MT with no human involvement. In this case, translators are only required to pre-edit texts so that these may perform better in MT databases, which leaves only a small market for PE and premium translation. Either way, in Davenport and Kirby’s (2015) view, individuals must decide how they wish to respond to the increasing level of automation, i.e. whether they wish to “step up”, “step aside”, “step in”, “step forward” or “step narrowly”, each step resembling a strategy to remain employable. With regard to translation, we expect that, for many years to come, TA levels will vary depending on factors such as language combinations and text genres, and also on which translators’ skills that will turn out to be automation-resistant.

In 2018, in a study for Microsoft, Hassan et al. (2018) claimed that Microsoft’s own MT engine translating news texts from Chinese to English delivers a quality level of human parity. This would probably resemble level 4 in our taxonomy, since the translation task in question was limited to a specific language combination and to a specific text genre. However, Hassan et al.’s study was met with scepticism. Similarly, Elon Musk, CEO of Tesla, has repeatedly claimed that Tesla’s vehicles are just about to be completely autonomous.

At the moment, vehicles with level-3 and level-4 features are being tested. An example is Waymo’s autonomous “robo-taxis” that have started picking up passengers in Metro Phoenix, Arizona, but these

can only operate in areas with perpendicular streets, with few cyclists and where the sun always shines (Godske 2019: 4). According to DA experts, there seems to be no doubt though that the future will see driverless vehicles almost everywhere, but since AI technology has not developed robots with social intelligence, it will still be a prerequisite that traffic rules (both written and unwritten rules, including typical behaviour of pedestrians and drivers) can be encoded by the systems (Godske 2020: 6). If the same holds true for TA, it might become a prerequisite that we adjust the way texts are written to make TA systems able to produce acceptable output. In technical documentation and translation, for instance, this is already the case, as texts are written using controlled languages and based on restrictive style guides, and as STs are pre-edited in order to obtain better MT outputs. Several studies have found that PE of MT is useful in terms of productivity and quality improvement measured in number of errors. However, Toral (2019), for instance, found that PE of MT results in texts with lower lexical variety and density and a higher degree of interference from the source language compared with human translations. Likewise, Macken et al. (2019) found that NMT systems produce new types of lexical errors such as non-existing words in the target language, which affects comprehensibility. Hence, new technologies seem to introduce new quality issues.

Most interestingly perhaps, there seems to be at least one significant difference between vehicles and translation technologies: with driverless vehicles, there will obviously be zero tolerance for errors and system failures that may cost lives. As for translation, however, it seems that society has already grown accustomed to imperfect translations, as e.g. raw MT and light PE are often deemed sufficient (Way 2013; 2018). However, this might have unfortunate consequences for languages in the long term – for instance, when texts and languages become impoverished and overly influenced by source languages (Toral 2019: 280). Also, TA systems may never be able to produce communicatively functional translations in those cases when a configuration of the ST structure and a direct transfer of semantic content may not suffice. At least, this may be the case as long as AI cannot provide machines with social skills of reflecting on and adjusting texts to people's knowledge and needs (Bolander 2019: 8). As only time can tell if we ever end up with translatorless translation systems that may be perceived as competitors or colleagues, it is very important that society in general and professional translators in particular do not unlearn the ability to understand, re-express and link cultures and languages.

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Figures

Figure 1:

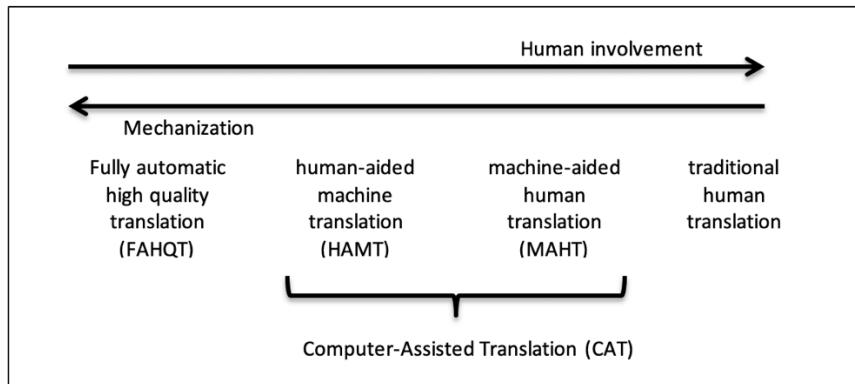


Figure 2:



Figure 3:



















Level	Name	Dynamic Driving Task (DDT)		DDT Fallback	Operational Design Domain (ODD)
		Sustained lateral and longitudinal vehicle motion control	Object and Event Detection and Response (OEDR)		
<i>Driver performs part or all of the DDT</i>					
0	No Driving Automation				N/A
1	Driver Assistance				Limited
2	Partial Driving Automation				Limited
<i>Automated Driving System (ADS "System") performs the entire DDT (while engaged)</i>					
3	Conditional Driving Automation				Limited
4	High Driving Automation				Limited
5	Full Driving Automation				Unlimited

Figure 4:

Driving automation terminology	Translation automation terminology
Dynamic Driving Task (DDT)	Dynamic Translation Task (DTT)
- Sustained lateral and longitudinal vehicle motion control	- Control of source text analysis and target text production
- Object and Event Detection and Response (OEDR)	- Error and inadequacy detection and response
DDT Fallback	DTT Fallback
Operational Design Domain (ODD)	Operational Design Domain (ODD)

Figure 5:

Level	Name	Dynamic Translation Task (DTT)		DTT Fallback	Operational Design Domain (ODD)
		Control of source text analysis and target text production	Error and inadequacy detection and response		
Translator performs all or part of the DTT					
0	No TA	Translator	Translator	Translator	n/a
1	Translator Assistance	Translator and System	Translator	Translator	Limited
2	Partial TA	System	Translator	Translator	Limited
"Automated translation system" (ATS "system") performs the entire DTT					
3	Conditional TA	System	System	Fallback-ready user (becomes the translator during fallback)	Limited
4	High TA	System	System	System	Limited
5	Full TA	System	System	System	Unlimited

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Figure 1: Hutchins and Somers' spectrum of translation methods as illustrated by Bundgaard (2017: 9)

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Figure 4: Driving automation and translation automation terminology

Figure 5: Levels of translation automation