The Language Engineer: A Transversal, Emerging Role for the Automation Age

La ingeniera lingüística: un perfil transversal y emergente
para la era de la automatización

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Abstract: This paper analyses the role of translators in a rapidly changing industry, which is strongly marked by digitalization and automation, and suggests the skills and competences translators will need to embrace to succeed in some branches of the industry of the (not-so distant) future. This research is based on an in-depth review of language-related positions in the current job market, as well as on recent survey-based research that sought to understand what roles translators are taking up currently, supported by web scraping of LinkedIn job data with Python. In today's globalised world, language-related services imply and encompass many more positions than translation alone. Different areas of specialisation are proposed, which may lead to successful and sustainable language-related positions in the age of automation by following and implementing the trends of the industry. We analyse industry trends and skills and competences that will play an important role in the (not-so distant) future job market, and suggest a new, highly-technologised, tech-symbiotic role: the language engineer. Language engineers are people with the required profiles to succeed in the automation age and will be able to commit to the multiple new, transversal language-related positions that appear as a result of recent technological developments. Numerous studies have drawn upon the "benefits" of technology in terms of productivity increase. Current market trends have also resulted in studies questioning the sustainability of the translation profession. Undoubtedly, technology changes our lives, but it's up to us whether it does so for good or bad. In our relation with technology, we can resist, cooperate or reinvent ourselves. We consider that defending a Luddite position (resistance to technology) will only bring negative consequences for the profession. Therefore, we suggest the role of language engineers, who will not only cooperate with and benefit from

technology but will also see their skills and competences augmented to meet industry requirements and be up to date with technological advancements.

Keywords: language engineer; decent work and economic growth; translation technologies; automation; natural language processing; human-computer interaction; digitalization.

Resumen: El presente artículo analiza el papel de las traductoras en una industria que evoluciona rápidamente por la digitalización y la automatización, y sugiere las habilidades y competencias que estas deberán adoptar para tener éxito en un futuro (no muy lejano). Esta investigación se basa en una revisión exhaustiva de las oportunidades de trabajo del mercado laboral actual con técnicas de minado de datos con Python, así como en encuestas recientes que pretenden comprender qué funciones están desempeñando las traductoras en la actualidad. En el mundo globalizado actual, los servicios lingüísticos son mucho más que solo traducir. Proponemos diferentes áreas de especialización que ofrecerán oportunidades laborales de éxito y sostenibles en la era de la automatización al seguir y aplicar las tendencias de la industria de los servicios lingüísticos. Asimismo, analizamos las tendencias del sector y las habilidades y competencias que serán clave en el (no tan lejano) futuro mercado laboral, y proponemos un nuevo perfil profesional, muy técnico y simbiótico con la tecnología: el de ingeniera lingüística. Las ingenieras lingüísticas son personas con los perfiles necesarios para triunfar en la era de la automatización, y serán capaces de ocupar las múltiples posiciones laborales, nuevas y transversales, que aparecerán como resultado de los recientes avances tecnológicos. Numerosos estudios se han centrado en los "beneficios" de la tecnología en términos de aumento de la productividad. Las tendencias actuales del mercado también han dado lugar a estudios que cuestionan la sostenibilidad de la profesión de las traductoras. Sin duda, la tecnología cambia nuestras vidas, pero depende de nosotras que lo haga para bien o para mal. En nuestra relación con la tecnología, podemos resistir, cooperar o reinventarnos. Consideramos que defender una posición ludita solo traerá consecuencias negativas para la profesión y, por ello, proponemos el papel de las ingenieras lingüísticas, que no solo cooperarán con la tecnología y se beneficiarán de ella, sino que verán aumentadas sus habilidades y competencias para satisfacer las exigencias del sector al estar al día de los avances tecnológicos.

Palabras clave: ingeniera lingüística, trabajo decente y crecimiento económico; tecnologías de la traducción; automatización; procesamiento del lenguaje natural; interacción persona-máquina; digitalización.

1. Introduction

Translation technologies have been transforming the industry for decades already. The discussion on translators vs. machines has been lengthy, focusing on questions as to whether the translation profession is a sustainable one or will be phagocytised by artificial intelligence (AI) and machine translation (MT) (Hutchins, 1997; Läubli, Sennrich & Volk, 2018; Toral, 2020; Briva-Iglesias, 2021). Recently, TAUS founder Jaap van der Meer (2021) suggested that by 2030 we would arrive at an era called "Singularity", where computers would take over the work of humans, and translators would no longer be

necessary. Shortly afterwards, Melby & Kurz (2021) responded, admitting the profound effects of technology on the language services industry, but suggesting that professional translators were here to stay. With each improvement of language technologies and/or the appearance of any new "breakthrough" (i. e., the advent of translation memories, the change from rule-based to statistical to neural machine translation), new discussions ensue, both from the point of view of professionals and academics. Pym (2013), for example, already anticipated that translators would need to change their skills in order to adapt to the industry of the future. There have been different studies and voices that shared this idea, suggesting that translators would need to specialise, and to acquire new skills and competences to stay relevant in a constantly technologized and digitalized industry (Rico Pérez & Torrejón, 2012; Nitzke, Tardel & Hansen-Schirra, 2019). To keep up with developments in the language services industry, academia has proposed new competence and skills models for the translators of the future, so that they can stay up to date and remain competitive in an environment of increasing digitalization and advances in automation (EMT, 2017; Hurtado Albir et al., 2020).

In 2020, Memsource published a report mentioning that, for the first time in history, 2020 was the year in which there were more post-editing than traditional translation projects on its platform (Memsource, 2020). This is an indicator of the pathway the language services industry is taking, with an increasing role for MT and post-editing (MTPE) in most market segments, not only in localisation, but also in the legal or the medical fields, which may suggest that these changes are happening industry-wide (Vieira, O'Hagan & O'Sullivan, 2021). The future that researchers have been talking about for years has already arrived, and the "technological turn" in the world of translation has already happened (Jiménez-Crespo, 2020). Nowadays, the translation profession can be perfectly seen and understood as a form of translator-computer interaction (O'Brien, 2012).

The effects of digitalization and automation in the language services world are noticeable and substantial, often leading to increased austerity, growing pressures to deliver projects as quickly as possible, and worsening conditions (Moorkens, 2017; Fırat, 2021; Pym & Torres-Simón, 2021). It is clear that technology has created a major disruption in the market, as evidenced by new workflows and the various studies mentioned above (Sakamoto, 2019). However, we consider that every change also offers room for opportunities, and technologies should not always be demonised because they may offer new professional prospects (do Carmo, 2020). Therefore, the aim of this article is

to propose new areas of specialisation that deviate from the traditional ones in the language services sector, as well as to repropose the title of language engineer to describe this role, as proposed by Sager in 1994.

In this paper, first we briefly review the current context of the industry, the major disruptive technologies, and the immediate effects they are having on the markets. Next, we discuss the potential industries, fields of specializations and job opportunities for the near future, which we anticipate to be many. Finally, we present the role and discuss the future of language engineers (see section 4 below for an elaborated discussion of this role), people dedicated to offering language services but with an updated and enhanced profile to make use and take advantage of technological advances in line with the industry of the (not-so distant) future.

2. The effects of automation on the industry

The language services world has undergone major changes in the last decade due to the continuous technological advances that have appeared and been introduced into the translation or localization workflows (ELIS, 2022). Nowadays, when we talk about translation technologies, a tool that has been making headlines recently or has been at the centre of the main controversies expressed on social media comes to mind: MT. However, in the translation industry, MT is just one small component of a wide range of tools that are used in some translation and localization processes with the aim of automating tasks and reducing costs. Among these tools, we can include not only computer-assisted translation tools (CAT), which use translation memories and digitalized term bases, as well as integrated MT, to facilitate and speed up the translator's task (Garcia, 2014), but also tools that are present even before the translator interacts with the text in the source language. Such tools come into play, for example, from the moment a client requests a quote for a translation using platforms powered by AI, where, by uploading a file, the format, the specialised domain of the text, and the number of words are identified. The platform then offers instantaneous automatic quotations that the client can accept with a click of a button to initiate a process that increasingly uses AI as a trigger, including the automatic assignment of the task to the translator with the best score in the translation agency's database in a given language combination, as well as the sending of an automatic email to the

selected translator. XTRF[1], Plunet[2] or Protemos[3] are some examples of this type of translation management software helping to automate workflows in the language services industry.

   Automation, which we conceive as an "automatically controlled operation of an apparatus, process, or system by mechanical or electronic devices that take the place of human labour" according to the Merriam Webster definition, is increasingly evident in today's labour market, as we can see in the large amount of research that this issue attracts from major organisations such as the International Labour Organization (ILO) (Chang et al., 2016) or the World Bank (Chuah, Loayza & Schmillen, 2018). According to The Global Competitiveness Report 2020, 46 % of current jobs in the OECD region are "at high risk" of automation (Schwab & Zahidi, 2020). The language services world is no exception, and the effects and consequences of the introduction of technologies in the professional workflow are beginning to be felt in all areas of specialisation, even in those that were thought to be the last bastion against technologies, such as literary translation (Guerberof-Arenas & Toral, 2020) or audiovisual translation (Díaz-Cintas & Massidda, 2019). In this section, therefore, we discuss some of the most notable effects of translation technologies today and comment on their effects and causes, as well as the direction in which we are heading in the (not-too-distant) future. Looking at the most recent literature on the impacts of technologies and automation on the language services world, the following elements stand out.

2.1 *Decrease of rates*

It has been shown that the different technologies used by translators facilitate their work, reduce cognitive effort and increase their productivity (Doherty, 2016). Paradoxically, this improvement in productivity, which should normally translate into an increase in turnover (if a translator can translate more words per hour, they will be able to take on more words throughout the day, which would multiply the words translated per week and should ultimately lead to an increase in income), is usually linked to a worsening of the working conditions of professionals in the sector (Jiménez-Crespo, 2017b; Fırat, 2021).

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[1] More information on XTRF can be found in https://xtrf.eu/es/ [Accessed 28/03/2022].
[2] More information on Plunet can be found in https://www.plunet.com/en/ [Accessed 28/03/2022].
[3] More information on Protemos can be found in https://protemos.com/ [Accessed 28/03/2022].

Large companies use these productivity "improvements" at the expense of translators. The reuse of previously translated segments stored in translation memories is deployed to apply discounts and increasingly accurate machine translation systems serve to justify a discount on the per-word rate by arguing that translators can translate faster by post-editing, i. e. modifying the machine translation proposals (Briva-Iglesias, 2020). This leads to a situation where, for example, a translator who translated 2,000 words 5 years ago and charged a rate of €0.12 per word, now translates those 2,000 words for €0.06 per word (which is a considerable reduction in the rate). It is worth stressing that these rates are only an example, and that rates can change depending on the language combinations and domains of the project. Nevertheless, according to our hands-on experience in the industry, these rates are concrete examples from the industry at the time of writing. Although the market for language services is growing exponentially due to globalisation and the volume of translation work increases year after year (NIMDZI, 2021), we cannot state that the translator who sees their rate reduced now receives more words to translate, and therefore their previous turnover is not assured.

Furthermore, methods and metrics like TER (Translation Error Rate) and hTER (Human-targeted Translation Error Rate) have been developed to calculate the hypothetical post-editing effort, i. e. the changes a translator would need to make to a raw machine translated sentence to achieve a professional, high-quality post-edited segment (Snover et al., 2016). These metrics are often used to calculate payment to translators. The post-edited segments are used as the gold standard, and the automatic metrics calculate the number of changes that a translator should make to the raw MT output segment, so it becomes identical to the gold standard. If five words need to be changed, then the translator would be paid more than if only one word had to be amended. When the required editing percentage of the segment is obtained, a specific payment rate is applied, similar to the one applied in the translation memory matches mentioned above. One of the problems with this method is that, when we talk about automatic metrics, as in translation quality assessment, we have to take into account that a sentence can be translated in multiple correct ways, and that a translator does not always make as few edits as possible (as a machine calculates it), but may repeat multiple additions and omissions until a final solution is reached in order to produce the best translation for their client, which would increase their post-editing effort compared to what automatic metrics would indicate. In other words, the technical and cognitive effort levels are not taken into account in this measure, and this could

result in the amount eligible for payment being less than the actual amount of effort to perform the task. The automation of these processes, either of the translation process itself through MTPE, or of the calculation of the editing percentage to adapt the payment, or both at the same time, is causing some translation stakeholders to reject the use of technologies (Sakamoto, 2019). We have also recently seen statements from national and international organisations of professional translators denouncing the use of machine translation in translation processes, such as that of the Association of Audiovisual Translators of Spain[4].

2.2 *Concentration of power*

The second element that is worth stressing, which is closely related to the previous discussion on rate reduction, is business concentration. Webber (2015) and Rinz (2020) argue that the concentration of power in the labour market results, regardless of the demographic group, in increased inequality and a worsening of working conditions and profit sharing. In recent years, the language services sector has been involved in major acquisitions and mergers of different types of companies in different market segments. Among the many mergers and acquisitions carried out in recent years, we highlight the two operations involving the companies with the biggest annual turnover, which may therefore have the greatest impact on the language industry. For this analysis, we rely on the 2021 ranking of the top 100 LSPs by Nimdzi, a leading language services consultancy (Nimdzi, 2020). On the one hand, in the specialised translation and localisation market segment, RWS (position 5 in the 2020 global turnover ranking, with USD 456.7 million per year) acquired SDL (position 4 in the 2020 global turnover ranking, with USD 480.7 million per year). On the other hand, in the audiovisual translation sector, which is booming thanks to large online content streaming platforms such as Netflix, Iyuno Media Group (ranked 11th in 2020 global turnover at USD 185 million per year) acquired SDI Media (ranked 10th in global turnover at USD 191 million per year). Pym & Torres-Simón (2021) commented on the results of another report done by Nimdzi in 2019, where language service providers with 250 employees or more increased their revenue immensely by

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[4] The complete statement can be found in the following link (in Spanish): https://atrae.org/comunicado-sobre-la-posedicion/ [Accessed 28/03/2022].

86 % from 2010 to 2016. Contrary to this, language service providers with fewer than 50 employees reported a negative growth. Regarding freelancers, they reported that their revenue growth was substantially lower than that of big LSPs. This information is also corroborated by other surveys of the language services industry (ELIS, 2022). What these commentaries show is that the market players that are benefiting from the large increases in turnover and growth of the language services industry are large companies, to the detriment of small companies or freelance translators. In Spain, Hoyos Seijo (2021) analysed translation industry data from the Spanish National Statistics Institute for the financial year 2020. According to these data, there were 10,466 individuals and legal entities in Spain who worked in the translation and interpreting sector during 2020. Out of these 10,466 individuals or legal entities, 9,247 (88.35 % of the total) were freelance translators. This means that there were 1,219 active translation and interpreting companies in Spain in the 2020 financial year, which represented 11.65 % of the individuals or legal entities dedicated to the language services sector. If we analyse the companies more in-depth, out of the 1,219 companies, only 10 (0.88 % of the total number of companies) had more than 50 employees, and 981 (80.47 % of the total number of companies) had fewer than 2 employees, which points to the great dispersion of the translation market and the high concentration of turnover in large companies, as indicated by previous research by Pym and Torres-Simon (2021) or industry reports (Nimdzi, 2021). The case of Ireland is identical, as according to data of the Central Statistics Office for the financial year 2019, out of 608 firms engaged in translation and interpreting activities, 593 (97.5 %) had fewer than 10 employees. Large companies are those that are seeing their revenue skyrocket according to the industry studies. According to Aarstad & Saidl (2019), small and medium-sized companies find it more difficult to adopt disruptive technologies and AI mainly because they have a lack of AI knowledge and consequently have to turn to external help, which increases costs and makes the adoption of these technologies not a priority and much more difficult to implement. Thus, large companies have the logistical and operational muscle to be able to implement new language technologies in their processes, such as neural machine translation, AI-powered supplier management or other technological solutions that are beyond the reach of small companies to escalate their profits and revenue due to automation. Implementing these new technologies is an even more difficult task for freelancers, who, as we have seen, tend to make up the bulk of the language services world. This situation is accentuated by the different

mergers and acquisitions, creating bigger companies, which may invest more heavily in automating workflows for cutting costs. Along these lines, Nunes Vieira (2020) suggested that translators are not afraid of technology per se, and that they often use it, but that they are afraid of how large companies use technology to their own particular advantage, and the consequences this may have on their working conditions. This raises the question of whether the danger to the translation profession is technology or questionable business practices, though this is not the focus of this article.

2.3 *Commodification and dehumanisation of the language services industry*

Another transformative element in the world of language services market is the emergence of AI-powered platforms that act as marketplaces (TAUS, 2017; 2018). In this article, we will use the term "digital labour platforms" (Fırat, 2021) to refer to these. Caruso (2018) warned about the use of positive terminology linked to such digital labour platforms, the developers of which advocate for collaboration between vendors or the democratisation of processes and workflows. It has been shown that these platforms often enable collaboration between crowdworkers in an attempt to exploit vendors or collaborators to maximise turnover (Scholz & Schneider, 2016). The ILO implied that the working methods implemented in most of these platforms were leading to appalling working conditions that were close to exploitative. This has been demonstrated in one of the few studies on digital labour platforms in the language services industry to date, which showed that, rather than democratising processes, they increased workers' dependence on the platform, leading to lower levels of bargaining power and agency (Firat, 2021). According to a report by CSA Research (Pielmeier & O'Mara, 2020), 89 % of freelancers responding to their survey indicated that they worked with such platforms on a regular basis. This, added to the growth of non-professional translation, as some language service providers hire people with only "language skills" or "looking forward to making some extra money", may worsen the situation (for more information, see Pérez-González & Susam-Saraeva, 2012; Alfer, 2017; Jiménez-Crespo, 2017a; Zwischenberger, 2017).

In the previous sections on the effects of automation on stakeholders of the language services world, it would seem that the people in charge of producing the translation were the most affected. However, they are not the only

ones. Digital labour platforms also greatly affect other stakeholders, such as project managers. With these new platforms, direct contacts between a project manager and a translator are reduced or even disappear, dehumanising and dampening traditional relationships in the language services industry. The outcome is even more ironic given that "communication skills" is usually presented as one of the most important for somebody in the role of project management. In addition, new workflows have recently emerged where translation tasks are released into a pool of open offers, which can be accessed by a set group of translators. These translators can then look at the details and conditions of the job and accept the task if they wish. The problem is that all translators accepted by the language service provider can access the same assignments and the acceptance of an assignment becomes a first-come first-served competition that dehumanises and accentuates the commodification of the profession. As if a language professional did not face enough complications in translating a text from the source language into the target language, they are now under pressure to wait for an "open offer" to appear on the client's platform in order to accept it and be able to work, often introducing a pressure that may result in not fully observing or analysing the conditions of the task to check whether the requirements are met. In addition, these tasks are often reduced to small projects of very few words, which increases the translators' effort even further (Moorkens, 2020). Moorkens (2017) uses the term "commodification" of language services to refer to the current system of suppliers, as translation is conceived as a "commodity", meaning that translators can be traded like any other commodity for elements such as rates, availability or quality. The "uberization of translation" is another term used to perfectly describe this context (Fırat, 2021). The latter term refers to the concept "uberization of work" proposed by Vercellone et al. (2018), in reference to the technology company Uber, which uses technological applications for new temporary and flexible professional relationships, reducing the stability of professional relationships and creating even more risks for workers.

In the language services sector, digital labour platforms affect translation processes substantially, from the lack of interaction between project managers and translators to not having enough time to study whether the conditions of a translation task are suitable for their profile for fear that someone else will accept the task more rapidly, or the moving from more stable labour relationships to a proliferation of freelancers and outsourcing (Moorkens & O'Brien, 2017; O'Brien & Rossetti, 2020; ELIS, 2022). Likewise, the proliferation of quality metrics and TQA scores are also key for these platforms,

as there are systems that automatically block translators who do not reach a quality threshold, leaving them out of the pool of job offers. Language services, which we consider a "situated action" where the context of production of the translation is relevant (be it ergonomic peripherals, adequate working conditions, usability of tools or user experience), could be severely affected by these additional pressures. For instance, a translator may have accepted a job in haste for fear that someone else would accept the task before them, not seeing that the deadline is in a couple of hours (due to the current urgency of the industry) and that may lead to an inability to produce good quality, subsequently harming the translator's reputation and possibly leading to loss of a client (Ehrensberger-Dow, 2017; Ehrensberger-Dow & Massey, 2014). In today's gig economy, where digital labour platforms are becoming more frequent and commonplace, we can already start talking about "humans as a service" (Prassl, 2018), saying goodbye to stable working relationships, and facing the risks of being our own bosses in this increasingly crowdsourced environment.

3. Methodology and results

In this context of widespread acceptance and introduction of disruptive technologies in the language services workflow, the focus is on the future: where is the industry going and what lies ahead? Will the language services industry continue to be a profitable and sustainable market with new technologies? What do graduates of translation degrees need to know? All these questions have been studied since the emergence of the first language technologies, but research on this topic has accelerated in recent years, with a focus on the skills and competences that translators will need in the not-so-distant future. Pym (2013) argued that translators would become post-editors. In the localisation sector, O'Brien & Rossetti (2020) noted that the digitalization of the industry has caused employers to increasingly look for tech-savvy linguists, who should have training in technology and IT skills such as file format management. Hao & Pym (2021) interviewed several graduates of a master's degree in translation who were already working, who commented that they would have preferred more training in "soft skills". Among other elements, communication skills, project management, critical thinking and risk management stood out. These new needs of employers are well reflected in the new competence and skills models presented in recent years, focusing mainly on

technological and digital components for the training of the translators of the future (for more information on the steps academia is taking to follow industry developments, see EMT, 2017; Nitzke, Tardel & Hansen-Schirra, 2019; Bernardini et al., 2020; Ginovart Cid, Colominas & Oliver, 2020). Despite the major impacts of technologies, digitalization and process automation in the language services industry, we believe that traditional positions (i. e. translator, localiser, project manager) will continue to be relevant and sustainable, in line with Melby & Kurz's (2021) article, although it is true that the position may be relegated to performing more repetitive, less creative and more management or quality control-oriented tasks in processes where a machine has been involved. Though, we do not believe that a period of "Singularity" will arrive any time soon (van der Meer, 2021).

The above-mentioned studies on the future of translation also indicated that PE was only 8 % of the language services offered in the localization sector by some of the respondents and that only 33-50 % of translation graduates actually ended up working in the language services world; the rest went into other industries (O'Brien & Rossetti, 2021; Hao & Pym, 2021). These results show us the great transversality of the sector, and the wide range of opportunities that exist in an industry that is growing year on year and which is expected to reach 57.7 bn USD in annual turnover by 2022 (Statista, 2022). This article therefore attempts to give visibility to those sectors that are usually hidden or relegated by the more traditional positions of language services. Though we consider that the call for specialisation in order to become more competitive in the traditional language services market is a valid and appropriate way to cope with the increasing automation, in this article we try to look beyond these traditional recommendations to offer and propose new areas, fields and domains where the human factor is an addition to the value chain and where human tasks cannot be substituted or substantially affected by machines, at least in the short term. Thus, our research question in this article is whether there are sustainable, human-centric career positions in the language services industry that will succeed in the automation age beyond those normally proposed (e. g. traditional translator and/or localiser).

In order to make these recommendations, we have used a mixed methodology, consisting of a manual annotation of research reports on the labour market, followed by a semi-automated analysis of LinkedIn job offers using natural language processing and data mining techniques with Python.

For the first part of the methodology, reports on leading industries and job trends in the current labour market have been collected. First, 16 reports have

been collected from LinkedIn (LinkedIn 2020), one of the world's leading job search platforms. Each report pertains to a region, providing a global perspective on labour market trends. LinkedIn creates the reports based on data from its users, who numbered more than 839 million in 2022. Secondly, we have also collected a report on the skills with the highest demand and the fastest growing industries in recent years elaborated by Randstad, a leading HR consultancy firm, which draws data from the job offers they receive and for which they need to source candidates (Randstad Sourceright 2022). Another report by McKinsey and Co., a renowned HR company, called *The Future of Work in Europe*, has also been analysed (McKinsey & Co., 2020). Finally, we also collected the 2021 and 2022 job trend reports from Udemy, one of the most popular online learning platforms today, which also draws its data from its users (Udemy, 2022; 2021).

Why did we use different types of reports? The aim has been to use different data sources to reduce the bias we may encounter when obtaining data from a single source. The job search platform (LinkedIn) gives us information on the most in-demand positions and job profiles and tells us the volume of hiring in each segment of the labour market. By having 16 reports from different regions, we have a more global perspective. The documents from the HR consultancy firms (Randstad Sourceright and McKinsey & Co.) tell us which job opportunities they receive from companies and for which they have to find candidates, i. e. sectors with real demand from employers. Finally, reports from the online learning platform (Udemy) provide us with information on what workers want to learn to enter new markets, either because their jobs require these new skills or because they see a promising future in these new competences. Thus, by working with 20 reports from different sources, we have a global view of the market because we consider both the interests of workers and employers.

The methodology used for the analysis was as follows. First, the PDF files of the reports were pre-processed in order to obtain plain text files. This was achieved by tokenisation and subsequent segmentation in Python. These plain text files were then dumped into the BRAT (Stenetorp et al., 2012) annotation tool and a manual annotation of potential industries was performed. With each mention of an industry in a report, the label "POTENTIAL_INDUSTRY" was added. Finally, the manual annotations were retrieved, and a table was made with the potential industries and sectors ordered from highest to lowest according to the number of annotations. In the 20 reports, a total of 29 potential industries were annotated, although in table 1 only those indus-

tries that were annotated more than 5 times are shown, as we consider that it is not necessary to include industries with fewer than 5 annotations due to space constraints and lack of relevance to the language services industry (e. g. "Real Estate" or "Logistics", with 4 and 2 annotations respectively). Table 1 allows us to identify the industries with the biggest potential in the future according to the reports consulted and let us relate them to the job opportunities in the language services industry.

Ranking	Industry name	Times annotated
1	Artificial intelligence (AI)	18
2	Digital marketing	16
3	Healthcare	15
3	E-Commerce professionals	15
3	Digital content creation	15
4	User Experience (UX)	13
5	Education	12
6	Data science	11
6	Specialized engineering	11
7	Customer service	10
8	Finance	9
9	Cyber security	8
9	Sales	8
10	Social media marketing	6

Table 1. Potential industries per times annotated in BRAT

After analysing the results in table 1 and relating the potential industries to the competences of translation graduates, we have decided to discard "Healthcare" (3rd position in the ranking), an industry that has gained relevance since the coronavirus pandemic but which is not very closely related to language services as a whole industry[5]. We have also merged "Digital marketing" (2nd position in the ranking), "E-Commerce professionals" and "Digital content

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[5] It is worth stressing, nevertheless, that language services experienced remarkably demand in the COVID-19 pandemic and in similar crisis situations, where multilingual communication is essential (Piller, Zhang & Li 2020).

creation" (both tied in 3rd position in the ranking), as we believe that they are similar industries that have to do with creative communication. Moreover, as "AI" (1st position in the ranking) is a very general computational field, which can pursue many different objectives (e. g. computer vision, machine learning, etc.), we have narrowed down the industry by focusing on the area of AI most closely related to language: natural language processing (NLP), which is a combination of linguistics and computing that aims to study the interactions between language and machines, and thanks to which machine translation engines, for example, are created. Thus, in this article we will analyse the first three resulting potential industries: "NLP", "Creative sectors in communication" and "UX".

The second part of the methodology consisted of a semi-automatic analysis of job offers from the 3 industries above to obtain information about positions and skills in these industries. For this article, a Python script has been developed to perform web scraping and to automatically collect 100 job offers from LinkedIn for each sector, as the platform allows searching by industry or sector. Therefore, we logged into a LinkedIn account, entered "UX" and "natural language processing" in the job search box, and collected the first 100 offers of each industry. As our third potential industry is made up of several sectors, we have collected 50 offers for "Digital marketing" and 50 offers for "Digital content creation". Thus, a total of 300 job offers were analysed. Although a larger number of job offers would have been better, we did not collect more offers because the analysis cannot be 100 % automated and requires some human intervention.

It is worth noting that most jobs on LinkedIn follow the same structure: name of the position, description of the hiring company, description of the position and requirements expected from the employee. Thus, we have performed two types of semi-automatic analyses in this second part of the study methodology.

First, we have exclusively analysed the titles of the positions, and compiled a table of positions by frequency. As each company indicates the title of the position they want, there are job offers on the same position with slightly different names, e. g. "UX Writer", "User Experience Writer" or "UX Writer / Editorial Expert". We manually homogenised these positions so that the automatic analysis counts these positions only as one identical occurrence. Table 2 shows the three most frequent titles in the 100 offers analysed in each sector.

Most frequent job titles in the NLP industry	No. of Occurrences
ML Engineer	16
Data Scientist	15
Computational Linguist	13
Data Annotator	13
Most frequent job titles in the creative communication industry	No. of Occurrences
Digital Content Manager	17
Digital Content Specialist	9
Social Media Content Manager	5
Most frequent job titles in the UX industry	No. of Occurrences
UX Writer	19
UX Researcher	17
Technical Writer	11

Table 2. Most frequent job titles per potential industry

This gives us an idea of the most common and in-demand profiles in the most promising industries. However, knowing only the name of the position provides us with superficial information, but we are interested in more detailed information. Therefore, in this second part of the semi-automatic analysis, we have compiled the descriptions of the "Qualifications"/"Requirements", "The Role"/"What will you do" section of all the 300 offers collected. Then, we have carried out the same automatic, lexical analysis to find the most frequent words from the collected corpus, which we have analysed from unigrams to 4-grams. The number of words analysed in each potential industry are as follows: NLP (49,043 words), creative communication (56,995 words), UX (58,791); resulting in a total of 164,829 words analysed for frequency collocations. For this automatic analysis, we have only looked for noun collocations (that is, only combinations of nouns), and we have deleted all the instances of other grammatical constructions, as the Python script retrieved 4-grams like "will be responsible for", which is a common wording of a job offer, but does not include information about skills or competences.

Table 3 shows the 3 most frequent noun collocations found in the job offers of each potential industry, ranging from unigrams to 4-grams.

Most frequent noun collocation in the jobs of the NLP industry	No. of Occurrences
Python	83
Machine Learning	68
Data security	27
Most frequent noun collocation in the jobs of the Creative communication industry	No. of Occurrences
Social media channels	58
SEO	47
Excellent writing skills	17
Most frequent noun collocation in the jobs of the UX industry	No. of Occurrences
User research	91
Qualitative and quantitative skills	48
Human-computer interaction	34

Table 3. Most frequent noun collocation per potential industry

In tables 2 and 3, we can see which are the most in-demand positions in the potential industries analysed, and with the noun collocations retrieved we can observe what the skills, requirements or tasks are of these positions. Thus, we have detailed information on the profile and skills that professionals will need in order to perform their jobs successfully or get hired. In the following section we discuss the results found and relate their relevance for professionals in the language services world.

4. Where is the industry going? Discussion of the results regarding new professional profiles

4.1 *Natural language processing (NLP)*

Of the skills or sectors with the most promising future, all the reports analysed unanimously agreed that the first position was for AI. As we are focus-

ing on NLP, a more specific domain of AI, the two most frequent job positions found in our analysis were machine learning engineers and data scientists. These profiles are technical, but we can see that academia in translation studies is taking into account the importance of programming languages such as Python, and is starting to train translators in this field (Krüger, 2021). Knowing Python does not, alone, equip people with skills in machine learning. Nevertheless, it is a good starting point.

In addition, NLP job opportunities are much broader, and we can see computational linguists and data annotators as some of the most frequent positions in NLP. To work in this industry, being a mathematician or a developer with strong programming skills is not mandatory (although training in programming can be a very interesting asset in today's market). There are two methods of operation of machine learning and AI algorithms: supervised or unsupervised learning. In supervised learning, labels must be assigned to certain fragments of documents so that the system can detect the elements to learn from. In contrast, in the unsupervised approach, there is no human intervention and the algorithms "learn" without labels. Currently, the approach that offers the best results is the supervised method, and this is where data annotators or computational linguists can begin to collaborate in document annotation or data curation for machine learning, with very different applications, ranging from the detection of professions with a higher risk of contracting diseases (Lima-López et al., 2021; Miranda-Escalada et al., 2021), to the detection of sexism in social media (Rodríguez-Sánchez et al., 2021) or the creation of automatic systems that recognize laws and legal elements in documents, which can then be applied in trials or to ease the tasks of a lawyer (Legg & Bell, 2020), among many other applications. Regarding MT, human experts can also help identify and fix the issues of both linguistic, gender, and racial biases currently reproduced by algorithmic bias, resulting in machine translationese (Vanmassenhove, Shterionov & Gwilliam 2021).

Thus, NLP is a field where more and more investment is being made, which is currently booming, and which can serve as a very interesting job opportunity for people with a graduate profile in translation and training and/or updating in technologies, whether in the writing of annotation guidelines, in annotation, in the field of named-entity recognition or even in the development and execution of algorithms. Likewise, with the rise of language technologies and their adoption by large companies, small organisations and enterprises, this expert profile knows both the world of translation and new technologies and is therefore aware of the strengths and weaknesses of both

worlds. These people can make use of their expert linguistic and cultural knowledge, their experience as language technology consultants, as well as their knowledge of the deployment of new technological processes in more traditional industries to recommend best practices and improve workflows.

4.2 *Creative sectors in communication*

According to Coursera (2022), "communication" will be the most in-demand personal skill in the future, deduced from the increase in requests for their online courses. This is in line with our results of the manual analysis, where we can find three different sectors in the top three of our ranking of potential industries, i. e. digital marketing, e-commerce professionals, and digital content creation. The increase in turnover of the language services industry is also very good news for those in the language services market. This can also be observed in the demand from graduates for increased training in communication skills (Hao & Pym, 2021). The constant globalisation of our society, where now all companies, whether large or small, even NGOs and public administrations need to interact with stakeholders all over the world, is an excellent environment for the development and enhancement of a booming professional market for language professionals.

Thus, with the noun collocations retrieved from the job offers we have identified different professional opportunities that diverge from the traditional positions of the industry and creativity is a vital component thereof. In these opportunities, the human factor will be essential and will add value to ensure a communicative success. These positions encompass services where creativity or in-depth knowledge of the target culture are essential requirements and, therefore, fields where machines cannot yet penetrate. We are talking about positions like digital content specialists, where services such as transcreation (where deep knowledge of the culture and locale of the markets in which a product is to be introduced is required), digital marketing (which requires not only linguistic knowledge, but additional excellent writing and creative skills in multimodal content creation) or videogame localization (where puns and word play are common and an in-depth knowledge of the gaming industry, the genre of the game, its brand and voice, as well of the target culture is needed to produce appropriate localization). Another professional opportunity that is increasingly growing due to the vitality and the importance of online marketing is that of SEO (search engine optimisation) and/or SEM

(search engine marketing) translation and localisation specialists (where basic translation knowledge is mixed with ad creation, keyword research, marketing campaign conversion research and SEO and pay-per-click tactics and strategies) (Pedersen, 2014; Katan, 2016).

4.3 *User Experience (UX)*

UX is one of the most important concepts researched in human-computer interaction (HCI). And HCI is a well-established discipline within computing, focusing on studying the interactions of humans with products, systems or tools (Dix, 2010). Given the current context of the language services industry, we can now consider the translation profession as a form of HCI. In our analysis of jobs, "UX Researcher" was the most common job in the UX industry. Thus, if we relate UX to the language services industry, we can then find niche work to improve the interactions of people with tools such as MT, regardless of whether users are professional translators, volunteers or end users. Traditionally, the MT field has tried to improve MT output by training larger models. In a field of certain saturation on the quality of MT, very little research has been undertaken on end users and UX (e. g., Koponen et al., 2020) and/or interfaces of interaction (Läubli & Green, 2019). MT developers have neglected the actual users of their systems and have focused mainly on technical advancements rather than on sociotechnical progress (Doherty & King, 2005; Olohan, 2011).

As our analysis of the reports has shown, with today's globalization and digitalization, UI and UX design and evaluation will be one of the most demanded positions and skills in the near future. Thus, evaluating, designing, and testing the different interfaces and interactions with new products may become a highly relevant and necessary step to take to keep improving the language services industry, not only from a technological angle, but also from a sociotechnical perspective. Our analysis shows that quantitative and qualitative skills are important requirements for researching UX.

UX research in the language services industry is not limited to interaction with MT systems, as we can see a proliferation of virtual assistants, smartphones and intelligent devices with which we communicate and interact on a daily basis (Clark et al., 2019). Studying, analysing and evaluating our intercultural communication and experience with such products, as well as improving and smoothening our interactions by creating utterances to help these devices communicate will be necessary over the coming years, opening

job opportunities for the professionals that know how to learn about, adapt to and work with this new type of devices. This utterance creation may perfectly fit into two of the most common positions in the UX industry: UX and technical writers, people who need to draft and edit technical documentation, review existing materials and deliver high-quality, fit-for-purpose content for local markets. They also need to have a highly specialised technical background for liaising with engineers and more technical-oriented roles, with the goal of producing texts that produce good user experiences on final users.

5. Labels really matter: the language engineer

Within translation studies, there have been multiple controversies over the terms used to refer to the different concepts within the discipline. If we move away from the product (texts) and processes (translation techniques, strategies and theories), and focus on the participants in the production of the product, traditionally, multiple terms have been used throughout history to refer to the people who practise the translation profession (Holmes, 1972). We have primarily talked about the "translator" as the person who carries out the task. However, this is also seen as a narrow term these days that does not represent the wide variation involved in the profession, including localisation, internationalisation, transcreation, subtitling, plain language editing and so on. For this very reason, the term "language services" has been used in this article to encompass all language-related activities, be it translation, localisation, internationalisation, transcreation, or any other service that a client needs to expand globally or reach new markets.

 One of the most widely used terms to refer globally to people in the language services sector in the recent history of translation studies has been "linguist" (McDonough, 2007). With this term, an attempt has been made to move away from the figure of the translator as a person who only translates, as they could be in charge of other types of services or tasks. However, "linguist" could also be used to refer to people who have nothing to do with translation, referring to an older use of the term to describe people who are exclusively dedicated to studying the particularities of language such as grammar, syntax, phonology, etc. Other researchers have also proposed more generic terms such as "cultural mediator" because the main task of these people is to convey a message and mediate between different cultures (Katan, 2013).

However, that term has also been criticised because it is sometimes used by employers to pay lower rates compared to the task of "translation".

More recently, with digitalization and the great technological advances described here, post-editing has gained a foothold in the world of language services and the term "post-editor" appeared for those people engaged in MTPE tasks. Yet, given that MT can be integrated with TM, it seems illogical to call somebody a post-editor when they might be engaged in both traditional translation (or CAT) tasks and MTPE for the same content. In the field of computing, the term "computational linguist" is also common for developers working with natural language processing, and although the term "linguist" is included, this term refers more to computer scientists who apply themselves to NLP. Another common figure in current processes in the language services industry is the "localisation engineer" (Esselink, 2002), a computer literate person, often with little multilingual knowledge, who plays a key role in the localisation process, and who is mainly in charge of preparing the different files to facilitate internationalisation (i. e. facilitating the localisation of content for different markets), preparing the translatable fragments of a software application, as well as reassembling, compiling and testing the output after the localisation process, ensuring that the localisation process is completed and there are no truncations or internationalization problems before releasing a product into the market, among other tasks. Also, with the new AI-powered digital labour platforms and the constant dehumanisation of the project management process of some large language service providers, people working with these platforms receive automated emails with the words "vendor", "resource" or "asset" and become mere statistics (based on translation quality in past projects, language combinations, availability, rates, etc.).

Thus, we see that the lens through which people are viewed greatly influences the choice of term to refer to what they do. The anonymous "vendor", "resource" or "asset" is used in contexts where the agency and value of the person does not have a very high status, whereas in the field of computing the term "computational linguist" appears to assign a higher status to the individual. There have already been attempts to revalue the profile of people involved in language services with a technological character, and there have been proposals to use the term "digital linguist" to describe a linguist with digital skills (Nitzke, Tardel & Hansen-Schirra, 2019). However, we are of the opinion that, due to the digitalisation of the language services world and the integration of digital tools in almost any current workflow (be it translation memories or technology management tools), the term "digital" is assumed

and intrinsic to anyone working in the language services industry today and is not particularly salient. What differentiates a linguist from a digital linguist? Is a linguist who uses a CAT tool a digital linguist already?

From this analysis, we can extract that there is a wide range of terms used in reference to professionals in the language services industry. The terminological review we have just undertaken also allows us to divide these professionals into two groups: i) professionals with knowledge of several languages who work mainly in the production of content (translators, linguists, localisers, just to name a few); and ii) professionals with computer skills who collaborate in technical processes, but who do not necessarily have language skills (e. g. computational linguists and localisation engineers). Though industry trends indicate that the combination of communication and technology will be increasingly needed, and the tech-symbiosis and technologisation of professionals is becoming more relevant, we have not found any profile that really fits these characteristics in a combination of both groups. For this reason, and after studying the major professional sectors arising from the new technologies, which a graduate in translation could join without problems by acquiring new technological competences or skills and adding them to their knowledge, competences and transversal skills acquired during their initial training, we suggest using the term "**language engineer**" for the profile of trained translators specializing in language engineering tasks. The term "language engineering" was already proposed in translation studies some time ago (Sager, 1994), and "language engineer" is a term currently used by companies like Amazon for employees with knowledge of linguistics and computational linguistics together. Thus, this is not a new term, but we recognize that it is underutilized for the current context of the language services industry.

Now, the question that arises from this definition is what are language engineering tasks? Throughout the article, we have seen the relevance of communication and its growing importance due to digitalisation and globalization. Without any doubt, the element that enables communication is "language" and hence this element is key to the term we propose to use as the most appropriate to the emerging, transversal profile of language engineer. The Cambridge Dictionary defines "language" as "a system of communication consisting of sounds, words, and grammar" in a more traditional sense of the concept, but also as "a system of symbols and rules for writing instructions for computers". This shows that, with new technologies, novel ways of understanding "language" have appeared, as well as new ways of working and interacting with it (through written texts, but also orally with audio, as

well as with automatic ways of processing and analysing data through NLP). Along these lines, the Cambridge Dictionary defines "engineering" as "using scientific principles to design and build machines, structures, and other things". We consider that modern language services fit this definition perfectly, whether we talk about "machines" (such as MT engines or any other type of NLP systems), "structures" (such as sentences and strings following fixed grammar and syntactical rules) and/or "other things" (ranging from virtual assistants or SEO/SEM ads, for example). In addition, "engineer" is a term with *value* (status and commercial) attached to it, and its use is regulated in many countries, which possibly explains resistance to using it for something linked with language/translation (traditionally seen as *low status/low commercial value*). It has been shown that job titles can significantly influence job evaluation (Smith et al., 1989).

This said, language engineers are people with a highly technologised profile, who are not afraid of and are willing to work with programming languages and AI, but also with profound knowledge of language and culture, allowing them to adapt to the new professional prospects arising from today's digitalization and automation by having a specific tech-symbiotic role. Language engineers are the necessary people in AI and technological projects where the knowledge of computation allows them to stay up to date with the techniques and methods employed, to understand the goals or aims of the project, and their linguistic, multilingual and intercultural experience enables them to make unique (and often missing) contributions towards adaptation to new markets and environments, enhancing and augmenting their skills, while at the same time becoming a priceless asset for any team working in NLP, the creative domains of communication, or UX.

6. Conclusions

We consider that every threat is accompanied by opportunities that may arise thanks to new training and professional profiles. After analysing the consequences of digitalization and automation in the language services industry and examining the different fields that the current market is targeting, we have been able to identify different sectors in which there is notable growth, and which are expected to become more relevant in the near future. Contrary to what some authors foresee as the end of human translation (van der Meer, 2021), we believe that translation is still a financially sustainable and future-proof professional career, which will continue to be relevant in the con-

stant globalisation of our society. However, it is true that traditional language services tasks may be relegated to more repetitive, less creative, and lower paid processes.

However, one of the objectives of this article is to highlight that these traditional tasks are not the only possible job opportunities in the world of language services, and that the profile of a person with a degree in translation includes transversal competences and skills that, well focused on a specific area of specialisation, can allow a "traditional translator" to also become a "language engineer" to offer added value in the global value chain of the automation age.

Recent technological developments in the language services world have been made without taking language professionals into account and have been more about technical changes rather than sociotechnical changes, without considering the real users of these developments (Doherty & King, 2005; Olohan, 2011). We are at the point where we need to get behind the wheel and know how to steer the direction in which we want research and industry to go, to set the limits of what is right and what is wrong, and the solution is not to accept the conditions of a large language service provider, reducing our bargaining power even further, but to keep up with updates, new developments, and what new technological advances allow us to do so that we can decide for our own benefit. This is the vital role of language engineers, demonstrating their added value to the value chain of the traditional language services industry by distinguishing themselves from both crowdworkers and traditional translators, bringing their language-based training, together with renewed technological skills, abilities and competences to escape from the commodification of translation. Language engineering tasks will be more demanded in the near future, and language engineers will be the appropriate people to perform them.

We consider that there are three attitudes that people in the language services industry can take towards technology: resistance, collaboration, or reinvention. We believe that the right way forward must be to embrace collaboration and reinvention. It makes no sense to reject technologies and start a Luddite crusade against AI and MT. That crusade is a battle we cannot win, even before starting it. Therefore, the solution lies in training for sectors with growing relevance for the future (and, as we have seen, already in the present) that have technology as the backbone and where the human factor is essential, such as in NLP, the creative sectors of communication or UX. What these areas offer is a towering professional opportunity for language engineers.

This is where we must keep up with the pace and rhythm of the market, to train new language engineers and give them the knowledge and skills that will enable them to stand out in the market, add to the value chain and work in a sustainable way in a sector that will be increasingly marked by automation and technology. Though suggesting new types of training is beyond the scope of this paper, training programs will certainly need to be looked at in the near future.

Acknowledgement

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